Success and Failure of Innovative Firms - The Role of Cooperation and Innovator Networks

Dissertation
zur Erlangung des akademischen Grades
Doctor rerum politicarum
(Dr. rer. pol.)

vorgelegt dem
Rat der Wirtschaftswissenschaftlichen Fakultät
der Friedrich-Schiller-Universität Jena

am 02.11.2016

von Diplom-Volkswirtin Tina Wolf
geboren am 27.06.1983 in Weimar

Gutachter: 1. Prof. Dr. Uwe Cantner
2. PD Dr. habil. Holger Graf
3. Prof. Dr. Dr. Thomas Brenner

Datum der Verteidigung: 02.03.2017

Table of contents

List of tables

List of figures

1. Introduction to the thesis

With this first part of the dissertation in your hand I want to invite you, as reader, to join me in analyzing the role of cooperation and knowledge exchange with regards to the performance of firms and especially with regards to the performance of young and innovative start-ups. You might ask: Why should this analysis even matter? Why is it worth joining the author here? Well, we live in a society where the pace of development increases year by year. Children start to go to school earlier, students study shorter, new products have to be established on the market much faster, firms need to be increasingly flexible and shall not risk to miss any market opportunity. This dissertation is picking out one of these aspects, specifically the firms that have to be fast and innovative to sustain the competitive forces in the market. By analyzing interactive behavior of innovative actors in the economy, I tried to shed light on the processes shaping inter-firm cooperation and the resulting innovator networks. I travel my way through this thesis by first taking a look at the factors that influence bilateral cooperation dynamics and then embracing a larger perspective by analyzing the role of complex social networks of innovators. Surprisingly, I find that mainly human characteristics like trust, social proximity, personal experience and social connections play a major role in shaping the innovative and economic performance of firms. This is a quite nice finding which shall remind us that firms are always a byproduct of humanity and human nature. Since innovativeness and networks are widely measured by means of patents, the last road I take in this dissertation is the one into the propensity to patent for young and innovative firms, a widely neglected group when it comes to the analysis of patenting behavior.

I kindly invite you as reader to enter into this work which took roughly eight years to be finished. Sure, I was writing this dissertation on my own but there have been many beloved people who supported me. Without them, this work would not have been possible. Firstly, I am deeply thankful to my doctoral father, who was always patient and had enriched my thesis with fruitful feedback and tremendously valuable ideas. My partner and my family were always standing behind me and supported me with everything they had. Your support and love means everything to me. I also thank my inspiring colleagues who

helped me by giving feedback, evaluating my ideas and sharing coffee breaks with me.

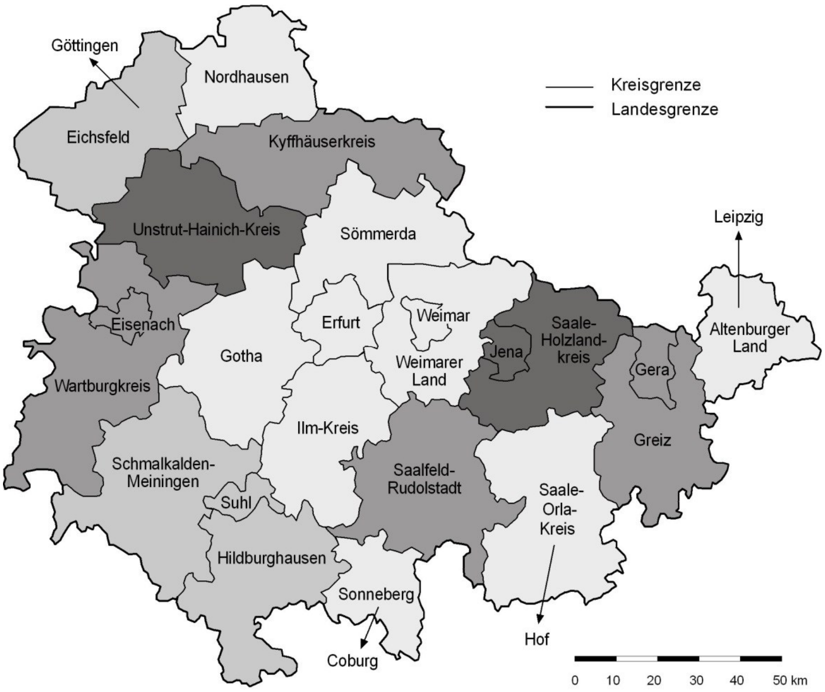
1.1 This thesis

This thesis is devoted to contribute to a better understanding of the role cooperation and knowledge exchange plays for the success and failure of innovative firms. Most of the work in this dissertation is based on the big shoulders of Josef Alois Schumpeter's ideas from 1912 – "The theory of economic development". Schumpeter was the first to delve into the process behind innovation and evolutionary processes in the economy. Some years later, Allen (1983) and von Hippel (1987) initiated empirical research on actors that cooperate in their knowledge production processes. The motivation for firms to cooperate, either with other firms or with research entities like universities or research institutes, lies in a couple of factors. Since innovation is a highly risky activity with respect to the dimensions of timing, costs and outcome, it is easier to bear when it is pooled (Bayona et al. 2001). Additionally, also the increased complexity of technical development requires a certain division of labour. According to the resource based view of the firm (Penrose 1959), which later on has been translated into the knowledge based theory of the firm (Grant 1996), a main part of the existing knowledge resources in the world lied outside the single firm. This translates access to external sources of knowledge into a main factor influencing the chances of a firm to be successful in its R&D activities (Cowan et al. 2006, Hagedoorn 2002, Freeman 1991). Therefore in today's world, and this stands in contrast to Schumpeter's idea of the single entrepreneur-innovator, innovation can be seen as a collective process of learning and recombining existing knowledge into marketable creations (Cantner and Meder 2007; Lundvall 1992; Kogut et al. 1992). However, cooperation might be rejected or even fail for several reasons. The first two papers (chapters 2 and 3) intend to go further into this direction and analyse factors that influence determinants for cooperation failure as well as determinants of cooperation dynamics. Chapter 2 analyses two determinants of bilateral cooperation failure, namely the lacks of intermediation and of reciprocity, two problems that might even lead a whole regional innovation system to fail (Cantner 2000, Cantner and Graf 2003). Before this chapter has been written there was basically no study on the determinants of cooperation failure, a research gap this paper started to fill. Since to date dynamic models of cooperative activities have been only analysed by a small group of authors (Balland et al. 2013, Broekel 2015, ter Wal 2014), the third chapter of this thesis adds to a new research stream where there still exists a large gap in the understanding of the mechanisms of cooperative behaviour and the dynamics of innovative networks.

Of course, the aforementioned processes of collective learning and exchange of knowledge between actors does not happen in a vacuum between only two partners. Many entities are active in the innovative environment and built up a network of actors which cooperatively engage in the creation of new ideas and then economize on the results – either within an existing firm or by founding a new one (Cantner and Graf 2007, Balconi et al. 2004). In these networks, knowledge spillovers which might be intended or unintended, facilitate the recombination of existing knowledge and therefore lead to higher innovative performance of its members (Edwards and Gordon 1984).

Entrepreneurial start-ups who bring up and disseminate innovation can be seen as one important driver of evolutionary economic change (Pyka 1999). However, the investigation of the role of new ventures in innovation networks and the role of innovation networks for new ventures is still in its infancy stage. Most studies see the innovator network as one regional factor influencing start-up (e.g. Jaffe 1986, Audretsch and Feldman 2004, Audretsch and Lehmann 2005, Cassia et al. 2009). However, none of the existing studies could directly connect the innovator network with the single start-up. By adapting Murray's (2004) observation on academic scientists to entrepreneurs, one can expect that an entrepreneur who is connected to the regional research community brings his scientific social capital into the firm and translates this into the firms' scientific social capital. Chapters 4 and 5 of this dissertation step exactly into this gap and connect the scientific social capital of start-up founders with the success of their firms. For Thuringia, which according to Granato and Farhauer (2007), can be subdivided into 12 travel-to-work areas (see figure 1-1), it is analysed whether there is an influence of the mere connection to the network as compared to an isolated situation as well as which network structure might be favourable and which position of the founders might help the firm to be more innovative and to survive.

Figure 1-1 Thuringia and its travel-to-work areas



Thuringian travel to work areas according to the estimations of Granato and Farhauer (2007)

In chapters 4 and 5 the innovator network is measured by means of co-patent applications, a quite common approach in innovation economics. However, studies on the patenting activities have shown that there exist tremendous differences in propensity to patent for innovative firms, depending on their individual characteristics (Scherer 1983, Bound et al. 1984, Brouwer and Kleinknecht 1999, Blind et al. 2006, Hall et al. 2012). Acs and Audretsch (1990) have shown that innovative start-ups show also significant differences in their characteristics. Notwithstanding, previous studies were not able to study the propensity to patent for young start-ups due to a lack of data (most studies use official statistical data bases where firms are observed when they have more than ten employees what is by far not often the case for start-ups in their first three business years). Chapter 6 intends to add to this research gap and analyses the determinants of the propensity to patent for innovative start-ups using questionnaire data. Additionally, be identifying the patents belonging to an innovative start-up via patent applications of the founder(s), this chapter is proposing a new approach for the identification of patents.

The next paragraph presents the structure of the thesis and summarizes the five main chapters.

1.2 Structure of this thesis

My thesis consists of five empirical studies. All of them have been presented on Jena Economic Research Workshops (JERW) of the doctoral research training group “The Economics of Innovative Change” (DFG RTG1411) as well as on national and international workshops and conferences including:

- DIME Workshop (Local and sectoral systems of innovations - Policy measures and possibilities, 19.-21. November 2008, Marburg (Germany)),
- EMEAA 2009 (6th European Meeting on Applied Evolutionary Economics, 21–23 May 2009, Jena (Germany)),
- DRUID Winter 2010 (DRUID-DIME Winter Conference 2010, 21–23 January 2010, Aalborg (Denmark)),
- ERSA 2010 (50th Anniversary European Congress of the Regional Science Association: Sustainable Regional Growth and Development in the Creative Knowledge Economy, 19 – 23 August 2010, Jönköping (Sweden))
- International Ph.D. course on Economic Geography (‘Geography of Knowledge, Networks, and Clusters', October and November 2012, Utrecht, Netherlands)
- 35th DRUID Celebration Conference 17-19 June 2013, Barcelona (Spain)
- 1st IWH ENIC Workshop (‘The Evolution of Networks, Industries and Clusters‘18-19 July 2013, Halle, Germany)
- 15th Conference of the International Joseph A. Schumpeter Society (27-30 July 2014, Jena, Germany)

The first empirical study named ‘Success and failure of firms' innovation cooperations – the role of intermediaries and reciprocity’ (chapter 2) has been co-authored by Uwe Cantner and Andreas Meder. I contributed to this paper by providing the research idea, preparing the literature, formulating the hypothesis as well as by exploiting the data. The other two authors provided support, mainly in guiding the estimations and by helping to interpret the results and draw conclusions out of it. This paper has been published 2011 in the peer-reviewed journal ‘Papers in Regional Science’ (Volume 90, Issue 2, pages 313–329).

The second study with the title ‘The Coevolution of Innovative Ties, Proximity, and Competencies: Toward a Dynamic Approach to Innovation Cooperation’ (chapter 3) has been co-authored by Uwe Cantner and Susanne Walter (born Hinzmann). I contributed to this paper mainly by conducting the empirical analysis and interpreting the results. My co-authors provided a literature review, prepared the database and together we discussed how to include our findings into the existing scientific landscape. After going through a blind peer review process, this paper has been finally accepted to the series ‘Knowledge and Space’ Volume 11 (Knowledge and Networks) which is forthcoming in 2017.

The third and fourth paper, ‘On regional innovator networks as hubs for innovative ventures’ (chapter 4) and ‘The selective nature of innovator networks: from the nascent to the early growth phase of the organizational life cycle’ (chapter 5) have been co-authored by Uwe Cantner. For both papers, I was doing the literature review, collected and exploited the data, processed the estimations and interpreted the results. My co-author helped in guiding to the focus of the paper and the estimation strategies, conceptualizing the paper and in finding interpretations of as well as conclusions from the results. ‘On regional innovator networks as hubs for innovative ventures’ is published in the working paper series Jena Economic Research Papers as JERP # 2016 – 006. ‘The selective nature of innovator networks: from the nascent to the early growth phase of the organizational life cycle’ is not published yet.

The fifth paper which I include into my dissertation thesis is called ‘Innovative start-up patenting: a new approach towards identification and determinants’. It is single authored, published in the working paper series Jena Economic Research Papers as JERP # 2013 – 023 and currently under review at ‘the Journal of Industrial Economics.

Table 1-1 presents an overview of my contribution to the papers combined into this thesis.

Table 1-1 Declaration of the candidate's contribution to the papers following §7Abs.2 PromO

Paper	**Authors**	**Idea**	**Conception**	**Empirical analysis**	**Theory section**	**Literature research**
Chapter 2: "Success and failure of firms' innovation cooperations: the role of intermediaries and reciprocity"	Uwe Cantner, Andreas Meder, Tina Wolf	leading	proportional	proportional	leading	leading
Chapter 3: "The Coevolution of Innovative Ties, Proximity, and Competencies: Toward a Dynamic Approach to Innovation Cooperation"	Uwe Cantner, Susanne Hinzmann, Tina Wolf	proportional	proportional	leading	slight	slight
Chapter 4: "On regional innovator networks as hubs for innovative ventures"	Uwe Cantner, Tina Wolf	proportional	proportional	leading	leading	leading
Chapter 5: "The selective nature of innovator networks: from the nascent to the early growth phase of the organizational life cycle"	Uwe Cantner, Tina Wolf	proportional	proportional	leading	leading	leading
Chapter 6: Innovative start-up patenting: a new approach towards identification and determinants	Tina Wolf	leading	leading	leading	leading	leading

1.2.1 Success and failure of firms' innovation cooperations - the role of intermediaries and reciprocity

There is rich literature dealing with cooperative activities of firms. However, no empirical study seems to have investigated the factors leading to malfunctions in cooperation projects in terms of a low likelihood of cooperation, low rate of success, and failed cooperation. The chapter attempts to fill this gap by investigating the possible presence of two problems in cooperation: the lack of intermediation and of reciprocity. Based on data gathered for firms in two German regions and one French region, we find that the success of cooperation projects depends on the perceived importance, rather than on the perceived quality, of intermediate actors. Hence, the major problem for intermediating suitable partners is more related to communication than it is a programmatic issue. Trust and reciprocity in cooperation between firms are found to be relevant ex-post in the sense of being the main determinant of failed cooperation projects.

Introduction

The theory of evolutionary economics argues that economic change is the result of the emergence and diffusion of innovations (Pyka 1999). Innovations are developed and introduced to the market by firms which are seeking for first mover advantages and (at least) temporary monopolies. Being innovative, however, requires technological knowledge, which may not be completely appropriable to the firm because some of its parts are tacit (Thornhill 2006). Additionally, uncertainty and risk involved in inventive and innovative processes are easier to bear when pooled (Baum et al. 2000, Bayona et al. 2001). Furthermore, the generation of innovations requires a recombination of existing knowledge (Cantner and Meder 2007) which may not be accessible to the single firm (Cowan et al. 2006). Access to such external knowledge as well as the potential to internalize knowledge spillovers is the rationale for firms to engage in R&D collaboration (Teece 1986, Nooteboom 1999, Griliches 1992). Thus, firms do not usually innovate in isolation but in collaboration and interaction with other organizations as other firms, universities, schools or ministries (Fagerberg 2005, Edquist 2005). By definition, organizations and institutions are components of systems for the generation and diffusion of innovations, namely the systems of innovation where special combinations of organizations and institutions can enhance a firm's ability to innovate and to compete successfully (Edquist 2005, Cantner et al. 2003).

Despite these presumed advantages, the establishment and continuation of cooperation-based knowledge exchanges face own problems that can affect the generation of new ideas in a significant way. Assume that the firm under consideration is willing to conduct R&D projects in collaboration with other actors (other firms, universities, research institutes). One may nevertheless observe a low level and intensity of cooperation-based exchanges. First, if there are enough potential cooperation partners available the firm may simply have failed to make contact with possible partners, presumably due to a *lack of intermediation*. This problem is just similar to the problems of asymmetrically informed borrowers and lenders in financial markets. Searching for an appropriate collaboration partner may cause high transaction costs related to gathering information about the existence of potential partners, their knowledge features and their reputations. If these costs are high or uncertain, actors may be reluctant and refrain from searching for potential cooperation partners. Intermediaries are entities whose function is to overcome this problem (Cantner and Graf 2003). Intermediaries in this sense are offices devoted to technology transfer, public agencies (regional politicians, business development agencies), conferences and know-how markets, collaborative research ventures, patents, other sources of information such as consultants and scientific journals, as well as employees' mobility and their function is to mediate contacts and to transfer knowledge between actors (Karlsson 1997). In this chapter, the three authors concentrated on 'chambers of commerce and industry' and 'business promotion entities' as intermediating actors. The presumed difficulties show two dimensions: the perceived importance and quality of intermediaries work. When they are in need of a cooperation partner, firms will only approach an intermediary if they are aware of them offering such a service and if they consider the services offered important. Thus, whether actors find an appropriate cooperation partner is a function of the alleged importance of intermediate actors. Therefore the authors hypothesize that a comparably higher perceived importance of intermediaries fosters the initiation of collaborative R&D projects (H2-1). With respect to the quality of the intermediaries' service, their ability to connect actors in a most fitting way serves as indicator. In the case of a low

fitting, collaboration is more likely to fail such that the success of collaboration can be seen as a function of the quality of intermediaries' services. The second hypothesis (H2-2) of this chapter goes in line with this argument and says that a higher perceived quality of the intermediaries' services fosters comparably more successful collaborative R&D projects.
Another explanation of a low level of cooperation refers to the lack of trust and reciprocity in firms' cooperative relationships, which reduces the incentive to engage in cooperation-based knowledge exchanges, the *lack of reciprocity*. The principles of reciprocity and fairness of economically acting persons as analyzed by Gouldner (1960), Güth and Yaari (1992), as well as by Cialdini and Trost (1998) can be applied to collective invention and innovation. There, cooperative activity in R&D, "is based on proven past performance and reliability of a cooperative relation, and thus has a rational basis even though it is no longer based on conscious deliberation" (Nooteboom 1999, p.797f.). In this context, reciprocity means that the transmission of knowledge by one actor is reciprocated by the other actor (Fehr and Gächter 2000). In other words, partners have to open their own knowledge stock to get access to the knowledge stock of the other. If there is a lack of reciprocity, the exchange of knowledge will not take place. Accordingly, two types of reciprocity problems can be distinguished, an ex-ante and an ex-post lack of reciprocity. If there is an ex-ante lack of reciprocity at hand, the actors are not cooperating because they have prejudices toward the potential partners and are doubtful about bi- or multilateral know-how streams (Cantner 2000). If, however, an ex-post lack of reciprocity is at hand, tensions between current cooperation partners lead to one partner withholding his knowledge stock or even breaking off the cooperation. Since the first type of a lack of reciprocity, the ex-ante type, could not be tested with the data at hand, the authors formulated a hypothesis only for the ex-post type of reciprocity problems. According to the argumentation above, the hypothesis goes as follows: The less trust collaborative firms have to their partners, the higher the probability that cooperation will fail (H2-3).

<u>Data and Method</u>

The data used was drawn from a questionnaire-based company survey in 2006 which was embedded in the research project "Second Order Innovations" financed by the Volkswagen Foundation. Firms were asked about development,

R&D effort, innovative and economic success, as well as cooperative behavior for the period 2003-2006. Altogether, 832 firms, whereof 529 are located in Northern Hesse (DE), 248 in Jena (DE) and 55 in Sophia Antipolis (FR) answered the questionnaire.
Since in the estimations, the dependent variables are of a binary or of a Likert-scale nature, we used logistic and ordered logistic regression methods.

Main Results
Hypotheses 2-1 and 2-2, which are related to the importance and quality of intermediaries, had to be rejected. This means that a lack of intermediation is not related to a higher likelihood of cooperative behavior as such and the quality of intermediation is not related to cooperation success. However, we found that, among the cooperative firms, the importance of intermediaries is positively related to cooperation success and there seem to be regional differences: First, in Sophia Antipolis the likelihood to cooperate in innovation seems to be much lower, which is surprising because this site was constructed by political will in order to enhance cooperation. Second, for Northern Hesse, the relation of intermediaries' importance on cooperative success appears to be much stronger, suggesting that the major problem for intermediation actors is communication rather than programmatic work. Both issues ask for further scrutiny by taking into account the characteristics of the respective region, the innovation system and/or the network of innovators which unfortunately was not within the scope of this paper.
Second, as to the problem of reciprocity in knowledge exchange, actors tend to break off cooperative projects because of missing trust to the cooperation partners, which supports hypothesis 2-3.

Contribution
While earlier papers on cooperative activities usually addressed the mechanisms of why they exist, how they work out and when they are successful, this paper goes into another direction and asks: Why may did not work? Basically, the intuition of asking for the problems that may hinder cooperation is taken from the theoretical construct of problems in systems of innovations as formulated by Cantner and Graf (2003). Here, three problems are enunciated in order to explain why the establishment and continuation of network-based

knowledge exchange (which is basically cooperative research) may not work. You may consider a number of potentially cooperating actors and after some time observe the level and intensity of network based exchanges to be considerably low. This may indicate that actors failed to know of each other and getting into contact — the problem of intermediation. Also, it may be the case that lacking trust and reciprocity in the actors' relationships reduces their incentives to engage in network exchanges – the problem of reciprocity. Or, the knowledge pieces that might be exchanged do not fit well to the network partners' knowledge requirements – the problem of complementarity (Cantner et al. 2008). The paper at hand was the first to address these kinds of problems on a basis of cooperative activities of firms and therefore contributes to a better understanding of this important facing of economic life.
In future research, it would be eligible to analyze the three problems as formulated by Cantner and Graf (2003) altogether and using a database which has been created for this purpose.

1.2.2 The Coevolution of Innovative Ties, Proximity, and Competencies: Toward a Dynamic Approach to Innovation Cooperation

Different dimensions of proximity have been identified as crucial factors for the formation of innovative alliances providing for efficient knowledge flows therein. However, the determinants that keep these linkages alive are yet to be explored. We take a dynamic approach to investigating the coevolution of cooperation ties and various dimensions of proximity between potential collaboration partners. Specifically, we highlight the predominant role of cognitive proximity for the continuity of innovation-oriented alliances and take into account that this proximity changes over time.
We observe partner switching more often than the repetition of collaboration. Neither knowledge transfer nor mutual experience with cooperation shows significant effects on repeated cooperation. Instead, we found that similarity (overlap) between the firms' knowledge bases, an imbalance of the reciprocal potential for knowledge exchange, the general experience the partners have with collaboration, and similarity in the popularity of collaboration partners favor cooperation.

Introduction

The relation between the proximity dimensions and the continuation of formed collaborations is by no means an unidirectional one (ter Wal and Boschma 2011). The proximity of partners' characteristics co-evolves along their cooperative relationship (Balland et al. 2015, ter Wal and Boschma 2011). Balland et al. (2015), Broekel (2015) and ter Wal (2014) recently have developed frameworks to dynamically analyze the evolution in networks. Ter Wal (2014) analyzed the role of geographic distance and triadic closure on network dynamics and found that the effect of geography disappears but the importance of social aspects increases over time. Conversely, Balland et al. (2013) find that social and geographic proximity are always important while cognitive aspects become more important later on. Broekel (2015) has additionally shown that cognitive, social institutional and geographical proximity do co-evolve over time. Having a look at the regional level, Cantner and Graf (2006) examined the network of innovators in Jena and found that technological proximity changes over time and that this comes with a high degree of instability in collaborative relationships. However, neither the mechanisms that cause change of proximities, nor the association with the multi-level has been sufficiently analyzed yet. We step into this research gap and take a dynamic perspective to describe the co-evolution of collaboration decisions, proximity and competencies. Cognitive proximity can be defined as a small level of difference between the knowledge bases of two actors (Boschma 2005). If the knowledge bases are quite similar, the potential to learn from each other is quite low. However, if the cognitive distance is too high, the potential to understand each other is reduced due to a lower absorptive capacity (Boschma 2005, Cohen and Levinthal 1990). Therefore, the level of cognitive distance presumes the success potential of collaborative ties. From a dynamic perspective, we can say that in order to step into collaboration, the knowledge bases have to overlap to a certain amount such that there are sufficient absorptive capacities. If partners move along the collaboration, knowledge is exchanged which leads to more and more similarity in knowledge bases until there is no knowledge to be exchanged anymore and the newness potential in this collaboration decreases (Balland et al. 2015, Nooteboom 1998, Wuyts et al. 2005). Therefore, the authors hypothesize that the relation between the cognitive overlap of two actors and the likelihood of their continued collaboration follows an inverse u-shaped curve (H3-1a). As Mowery et al. (1998) argue: the sheer overlap of knowledge might not measure the full learning potential in an innovative collaboration. Therefore, in this chapter the reciprocal potential –which measures in how far the collaboration partners can reciprocate the amount of new knowledge they offer to their partner– is measured in addition to the overlap (Cantner et al. 2011). According to Cantner and Meder (2007), we hypothesize that the reciprocal potential between two actors is positively correlated with the likelihood of their continued collaboration (H3-1b). Besides these two factors, we also argue that reciprocal learning (we also call it knowledge transfer) plays a major role in the sustainability of collaborative activities (Hamel 1991, Khanna et al. 1998). The collaboration partner who learns first gains bargaining power since the lagging partner becomes less attractive. Therefore, we hypothesize that knowledge transfer between two actors is negatively correlated with the likelihood of their continued collaboration (H3-1c).

Also social proximity or distance; associated with trust, the establishment of mutually agreed social norms and control over undesired, non-cooperative behavior (Boschma 2005, Granovetter 2005, Walker et al. 2003); shall play a role in the dynamics of collaborative relationships (Dahlander and McFarland 2013, Gulati 1995). Social proximity develops along with repeated interaction in form of successful cooperation which leads to trust that can explain the persistence of cooperation alliances (Gulati 1995, Mowery at al. 1998). Taking these arguments together, we formulate the related hypothesis as follows: The likelihood of continued collaboration between two actors increases with their prior common experience (H3-2).

Besides cognitive and social proximity, competence can be a factor influencing the evolution of collaborative relationships. It has been found that innovative capabilities and experience in managing collaborative agreements can increase an actors' attractiveness as collaboration partner (Ahuja 2000, Gulati 1999, Stuart 2000). Therefore, potential partners who had more collaboration in the past might be more attractive. If we assume that the condition of reciprocity needs to be fulfilled for repeated collaboration, we expect the likelihood of continued cooperation to be positively associated with the combined innovative and collaborative experience of both partners. Therefore, we hypothesize that the greater the general inventive or innovative experience of both partners is, the higher is the likelihood of their continued collaboration (H3-3a) and the greater the general collaboration experience of both partners is, the more likely it is that their collaboration will continue (H3-3b). Additionally to the experience the partners bring into the innovative collaboration, the number of collaborative ties that the actor has established also determines the number of opportunities for additional collaborations. Barabási and Albert (1999) have shown that in the evolution of networks, central actors tend to become more central over time. This phenomenon is known as preferential attachment and might be explained by the broad access that central actors have to information about potential partners and by the high visibility that central actors have for other potential partners (Ahuja 2000, Barabási and Albert 1999, Dahlander and McFarland 2013). Central actors are more likely to find that their invested efforts are reciprocated by actors who exhibit the same degree of popularity. If collaboration is to continue, then that power needs to be equally distributed among the partners so as to avoid unilateral dependence (Hamel, 1991). Since partners are therefore more likely to connect with each other and to maintain this connection if they possess a similar number of collaborative ties (Dahlander and McFarland 2013), we hypothesize that: the more similar the popularity of two actors is, the more likely it is that their collaboration will continue (H3-3c).

Data and Method

In order to analyze the hypotheses stated in the chapter introduction, we use information from patents that have been filed between 1978 and 2010 by German applicants in the field of Biotechnology. The data was gathered from the OECD REGPAT (January 2012) database and covers patent applications to the 'European Patent Office' and the 'United States Patent and Trademark Office'. The correct matching of one applicant's patents has been done by using the Harmonized Applicants' Names (HAN) database. Since we wanted to analyze the development of collaborations, we created an unbalanced panel where we observe collaboration-pairs and the development of their relationship over time. The basic sample consisted of 197 firms that have applied for patents with partners in the timeframe analyzed. If a firm was co-operating more than once in the whole time span (91 firms out of 197), we paired it to each of the potential cooperation partners that were active in the pool at that time. The size

of the pool of potential cooperation partners amounted to a maximum of 2,369 potential partners such that over the whole time span, we identified 321,683 possible dyads of which 293 were actually realized.
In our analysis, the decision to cooperate with a certain possible partner at a certain point in time is a binary one. Therefore, we applied a logistic model and a random-effects panel model and - to obtain robust standard errors - resampled the original dataset 1,000 times.

Main Results

In a descriptive analysis, we find on the one hand that a repeated collaboration with only one partner seems not to be a dominant behavior in our sample and that repeated links are not very probable. With our estimations, we intended to find out more about the incentives to form and repeat alliances. On the side of cognitive proximity, we analyzed three dimensions – overlap, reciprocal potential, and knowledge transfer. We find that a higher overlap in the knowledge bases of the partners and in line with this a small reciprocal potential leads to a higher collaboration probability which contradicts the assumption that knowledge diversity positively influences the development of cooperation. Regarding social proximity we analyzed the connection between the propensity to cooperate and prior common experience. Since we could not find significant coefficients, we have to state that in our database social proximity does not seem to be an incentive for collaboration. However cooperation experience, in general, has a significant effect. The third dimension analyzed was similarity in competencies. We find that the probability for two potential partners to collaborate is higher if both partners have the similar level of experience and popularity.

Contribution

This study aimed at the analysis of the coevolution of cognitive proximity, social proximity and similarity in competencies and their role in the development of collaboration in innovation. First, it contributed to the debate, whether innovative networks are rather stable or volatile. What we find is that firms rather switch their cooperation partners and do not persist in repeating collaboration with the same partner. This goes in line with the analyses by Wuyts et al. (2005) and well as Cantner and Graf (2006) who have also shown that collaboration between two partners tends to be rather a single than a repeated event. However, they argue that it is the search for diversity in knowledge sources which leads them to be less faithful. We instead find that they are looking for partners with similar knowledge bases and competencies which lead us to expect that there is some other motive for the change in collaboration partners. This leaves space for future research. In sum, we argued that this study was a further step into disentangling the co-evolution of proximity in R&D collaborations and the repetitiveness of ties. Also, although much work has been done to identify factors that lead to tie formation and breakup, most studies on innovation networks relied on static approaches. In this chapter, we contributed to the literature on dynamic analyses on innovation networks.

The methodology applied comes with some limitations that shall be mentioned here. Since we can only measure collaboration that led to a patent, we might underestimate the actual number of linkages in the network. Also, informal ties cannot be detected here. The study only analyzed firms that are active in the Biotechnology sector. In order to secure the generalizability of the results in a future study, one could conduct this analysis in other sectors. Since we only analyze the micro-level of the network, we may also resort to macro-level analysis and test the effects of the overall network, not just of bilateral cooperation.

1.2.3 On regional innovator networks as hubs for innovative ventures

A wide body of literature has focused on the evolutionary process behind firm growth and survival. Growing interest is devoted to the variable 'location' as critical factor, shaping firm performance. However, less attention has been paid to the region-specific characteristics e.g. university-based knowledge spillovers that may play a relevant role in determining the growth and survival of a firm. This paper extends this approach to the regional innovator network promoting region-specific knowledge spillovers and shows that the firm's individual probability to be innovative and connected to the innovator network positively influences the chances of this firm to survive.

Introduction

Economic change is a selective process where firms with competitive advantages (the fittest firms) gain market share while the other firms lose and will be selected out of the market at a certain point in time. The innovation process, however, is a complex sequence of events that lead to something new to the market (Edwards and Gordon 1984, Kline and Rosenberg 1986). Since one firm or one inventor cannot hold all necessary knowledge in the world to find relevant new technological combinations, innovation activities must be collective and social processes, where various pieces of knowledge are combined into innovation (Lundvall 1992, Doloreux and Parto 2005). The ability of a firm to generate innovation is seen as a key driver for economic success of firms. This relation has been empirically proven by several authors (e.g. Jaffe 1986, Hall and Bagchi-Sen 2002, Thornhill 2006). Since not all knowledge pieces which are relevant for the generation of innovation might be in the immediate reach of a firm, personal knowledge spillover-producing interactions are of a special relevance (Cantner and Meder 2007, Cowan et al. 2006, Breschi and Lissoni 2006). These interactions occur in interpersonal contacts between employees of firms, of research institutes or of universities, students or self-employed persons who actively conduct research. Per definition, this network comprises persons who cooperatively engage in the creation of new ideas and then economize the results (Cantner and Graf 2007). This economization happens either within an existing firm or by the formation of a new venture.

Such a social network can be defined as innovator network (IN). The research-oriented relationships between the actors indicate knowledge transfers and exchanges respectively knowledge spillovers which form the basis for new ideas facilitated by the recombination of existing knowledge (Edwards and Gordon 1984). However, it is not just their innovative effort which brings them together. They may, of course, be partners in formal research cooperations between several firms. Additionally, they may be former colleagues, thus innovator mobility may play a role. It can also not be excluded that they may know each other from playing tennis in the same sports club, eating in the same restaurant or from bringing their little ones to the same nursery.

For a firm that has been founded by or employs an actor who is socially connected to the innovator network, the connection to the IN promotes the expansion of its knowledge base and it's potential to innovate. Consequently, an actor

who is connected to the IN can provide an important prerequisite for the generation of innovations and therefore it may serve as an important facilitating device for long-term firm survival of a firm (Thornhill 2006).
Therefore we hypothesize that: firms that are connected to the innovator network are more innovative than non-connected ones (H4-2). Furthermore, we hypothesize that innovative firms survive longer than non-innovative firms (H4-1) and this effect is driven by the connection to the innovator network (H4-3).

Data and Method

For this chapter, a biographical firm dataset has been constructed based on two data sources. Data on incorporations founded in the years between 1993 and 2006 in Thuringia was gained from the German commercial register. The second one is patent data comprising all German patents applied for at the German Patent Office in the time period between 1993 and 2004. For a survey population of 12,505 founders and their 7,016 companies, we have information on the founders (date of birth, name, surname, academic title, address, gender) and on the firms (date of founding, date of closing, trade name, location, legal form, spin-off or not, industry).
The second database was drawn from the German Patent Office, where we used information on patents that have been registered between 1993 and 2004. Here at least one Thuringian inventor (the assignment was made by postal codes of inventors' address) should be listed on the patent. The resulting data base contains information on 6,969 inventors (name, surname, address) and 5,381 patent applications (IPC-Code, name, and address of the applicant, application date and year). Using this data, we could create a one-mode affiliation network if innovators in Thuringia where the connection was defined by co-applications of patent.
By matching names of firm founders with names of inventors in the innovator network, we combined these two databases. All firms where we could find a match have been identified to be innovative. By analyzing the network, we were then able to find out whether the founder of those firms that are innovative are isolated from or connected to the innovator network.
Survival and the number of patents applied for were the two main dependent variables. For all estimations where survival was the dependent variable, we

applied Cox's proportional hazards model (1972) which gives a valid estimate of the survival rate for data which is right-censored and left-truncated. Since the number of patents applied for is a count variable which is highly skewed to the left, we applied negative binomial regression methods when the dependent variable was the number of patents (Greene 2003, Cameron and Trivedi 2013).

Main Results

In this chapter, we intended to find out how much the performance of a newly founded venture relies on the influence of the innovator network. The analysis was conducted in several steps. In a first one, we wanted to prove that our sample behaves like other samples that have been analysed before by other researchers. Therefore, we tested whether the performance of the firm, measured in terms of survival, positively depends on innovativeness, measured as number of patents applied for. Using Cox's proportional hazard model for a sample of 2,199 incorporations, we find that indeed the hazard ratio is reduced when firms are innovative. The next step was to test whether within the group innovative firms (442 out of 2,199 incorporations), we find differences in innovative performance (number of patents applied for) between connected and isolated actors. Indeed connected firms show up to have significantly more patents than isolated ones. Since we have hypothesized that not just being innovative but being innovative and connected to the innovator network leads to a high firm performance, we go one step further and combine these two aspects. By regressing different firm characteristics on a dummy take the value of one if the firm is innovative and connected to the innovator network at the same time, we create a variable which is describing the probability to be innovative and connected to the network, dependent on certain characteristics (fitted value). This probability is then, together with several control variables, regressed on the hazard rate of the firm, which comes out to be reduced by this variable. Therefore, we could provide evidence for the overall hypothesis of this paper, that being innovative is an important prerequisite for firms' survival but that this is also moderated by the connection to the innovator network.

Contribution

While earlier papers on entrepreneurial ventures usually analyze the two aspects of innovation and the innovator network separately, in this chapter we

make a first attempt to combine these two. Thanks to the combination of data from the commercial register with data from the German Patent Office, we were able to include the innovator network not just as one (external) factor influencing firm success, but we could integrate it into the firms' resources.
Regarding the results, we could show that innovative firms have higher chances to survive as compared to non-innovating firms. Additionally, this shows up to be driven by the connection to the innovator network. By being a capital company, by the region, the firm is located at and by the stage of the respective industry's life cycle.

1.2.4 The selective nature of innovator networks: from the nascent to the early growth phase of the organizational life cycle

Earlier studies have shown that entrepreneurs play a key role in shaping regional development. Innovator networks where these entrepreneurs are members of have been identified as one among many critical factors for their firms' success. This paper intents to go one step further and analyses in how far differing characteristics of these networks lead to different firm performances along the early stages of the organizational life cycle (nascent stage, emergent stage, early growth stage). A sample of 149 patenting (innovative) firms in Thuringia is analysed, using data from the commercial register and the German patent office. The results show that there is an inverted u-shaped relationship between the chances of a firm to survive and the connectivity of the network the firms are connected to but only in the later stage of the early organizational life cycle; while the structure of the ego-network never plays a role. A quite central position in the network shows-up to be unfavourable.

Introduction

The regional innovator network (RIN) and his functioning have been defined already in the introduction to chapter 4 of this dissertation. Chapter 4 has also shown that the connection to such a network can be favourable for the survival of young and innovative companies since they might receive more knowledge spillovers, which in turn have been shown to positively influence firms' innovativeness (Feldman and Audretsch 1999, Meagher and Rogers 2004) and productivity growth (Griliches 1992). If we consider start-ups, connected to the

RIN, specific effects of network structures on the organizational performance may play a role. Dependent on the structure of the network, spillovers between the nodes (actors in the net) may be eased or hindered. However, an analysis of the relationship between the selectivity of the innovator network and start-ups' survival cannot be conducted independently of the organizational life cycle status of the individual firm (Hite and Hesterly 2011). Therefore, chapter 5 of this dissertation asks the following research question: What role does the structure of the innovator network, the position of the founder(s) in the network and the structure of the founder's ego-network play for the survival of firms in the early stages of the organizational life cycle?

The early stages of the organizational life cycle considered here are the nascent stage, the emergent stage and the early growth stage. The nascent entrepreneur is experimenting with different business ideas, starts to take care of the first stages in the founding process and starts to collect resources along with applying for financial funds and therefore there seems to be no real strategic orientation (Kessler and Frank 2009, Cantner and Stuetzer 2013). Due to this fact, other factors than the social scientific network might play major roles for the development of the young firm (H5-1a, H5-2a, H5-3a).

After the legal founding of the firm, the emergence stage begins where the firm starts to act on the real market. In this phase the only strategic goal of the firm is not to die, thus to survive the selection process (Gartner et al. 1992, Hite and Hesterly 2001). In this phase, the founders need to know everything that is going on in the technological field. The best conditions for this can be found in quite dens networks and if he takes there a central position with a quite closed ego-network (H5-1b, H5-2b, H5-3b).

However, in the early growth stage, the firm is settled in the market, starts to make real strategic decisions and therefore requires a broader scope of resources (Hite and Hesterly 2001). When the firm develops and enters into the early growth stage, the advantages of a very cohesive network may turn into disadvantages and the fragmented network and many possibilities to broker and control knowledge flows becomes more appropriate (H5-1c, H5-2c, H5-3c) (Hite and Hesterly 2001).

Data and Method

As for the research paper which is presented in chapter 4 of this dissertation, we used a biographical firm dataset which has been constructed based on two data sources. Since it is basically the same data base as in chapter 3 of this dissertation, please refer to the data description in chapter 1.2.3.

Using this data, we could create one-mode affiliation networks of innovators. In contrast to chapter 4, where we had networks for the whole innovative scene of Thuringia, in this chapter we crated 12 regional innovator networks according to the travel-to-work areas of Thuringia (see figure 1-1) and analysed whether this connection influences the chances to survive of young and innovative companies.

The dependent variable in the estimations was survival/the hazard ratio. Therefore, we applied Cox's proportional hazards model (1972) which gives a valid estimate of the survival rate for data which is right-censored and left-truncated.

Main Results

Over all analyses, we find that there is no influence of the network structure, in the year of founding and three years before that. However, we were able to identify significant effects five years afterward. The relationship between survival of firms and connectivity of their networks seems to be inverted u-shaped. This indicates that Burt (1992) and Coleman (1988) could both have been right: high fragmentation and high connectivity can be favourable conditions. Future research should look at the determinants which are influencing which kind of network is favorable for a firm. Potential determinants for this are the sector the firm is active in, the stage in the industry life cycle or the age of the firm.

Having a look at the ego-network, which is basically the influence of opportunities to broker knowledge on firms' survival, we find no significant results.

With respect to the influence of the founder's position in the network on firms' success, we looked at his centrality and on his membership to the main component. We find that being a member of the network's main component has a negative influence on the survivability of firms in the early growth stage. For Eigenvector centrality, we find a small negative effect indicating that a central position in the innovator network is not too favorable in the nascent stage of the firm' life.

Contribution

The research paper could contribute to the research on the influence of innovative networks on firm success. It is new that an analysis sees the innovator network as social scientific capital of the founder and integrates it as resource of the individual firm. Additionally, the interesting result that there seems to be an inverted u-relationship between the connectivity of the network and the chances to survive of a young and innovative firm might be reheating the debate on the opposite views of Coleman and Burt.

1.2.5 Innovative start-up patenting: a new approach towards identification and determinants

There already exists broad literature investigating small and innovative firms in many respects. However, there have been few attempts to assess this group of firms' propensity to patent or its patenting activities. This chapter intends to fill that gap. By applying a new approach to account for young and innovative companies' patents, this paper avoids an undercounting of small firm patenting, which has been a limit of most of the previous studies. A dataset is used that comprises information on R&D, capital stock, state promotion etc. for 534 Thuringian firms in their first three business years. The results of the zero-inflated negative binomial regression analysis suggest that patenting is an activity of science-oriented, cooperative young firms that are conducting R&D even before the firm has been launched.

Introduction

Although they come with various limitations, intellectual property rights or patents have been proved to be a useful indicator for innovative performance in innovation studies (Griliches 1990). However, it has been shown that not every firm has the same propensity to patent, which means that given the same amount of innovation intensity, different firms may still differ with respect to patenting intensity (Scherer 1983, Brouwer and Kleinknecht 1999). Although there have been many studies on the question in how far large and established firms differ in their propensity to apply for a patent and on the determinants influencing this (e.g. Scherer 1983, Bound et al. 1984, Brouwer and Kleinknecht 1999, Blind et al. 2006, Hall et al. 2012), few attempts have been made to analyse differences in the propensity to patent for small and innovative firms, especially for innovative start-ups. This paper is devoted to step into this gap and asks: What are the determinants of innovative start-ups' propensity to patent? Five factors can be identified that might explain differences in the patenting behavior of new ventures.

Regarding pre-founding experience, it can be expected that founders who have applied for patents before founding a firm show a higher propensity to go for patents after founding the firm. This might be due to the fact that they have experience with the patenting process, know about the value of protecting intellectual property from imitation or maybe they just have more innovative business ideas (Arundel 2001, Harter 1994, Walter et al. 2010, Dosi 1997). Therefore the first hypothesis states the following: Patenting behavior is path-dependent in the sense that patenting in the preparation process for founding the firm increases the patenting intensity after the firm has been founded (H6-1).

Since Cantner and Kösters (2009) find that R&D subsidies for start-ups come with an additionality effect such that subsidized start-ups show a higher patent output as compared to non-subsidized ones, the second hypothesis is that: Start-ups receiving state promotion show a higher propensity to patent (H6-2).

Venture capital is a hot topic in entrepreneurship research in these times. Cordes et al. (1999) find that the costs of applying and reinforcing a patent were a reason for young firms to not apply for a patent and Graham et al. (2010) found that financial constraints are a significant barrier for young firms to patent. Firms receiving venture capital might be in a more relaxed situation such that it can be hypothesized that start-ups with a venture capital budget are more innovative, can more easily apply for patents and will, therefore, patent more (H6-3).

Cooperative R&D activities are usually more successful as compared to individual R&D (Cowan et al. 2006). Also since patenting services serve as a vehicle for the formalisation of technology exchange agreements it can be expect firms engaged in R&D collaboration projects to have an above-average propensity to patent since patenting may make it easier to treat a firm's knowledge as a tradable asset when it comes to negotiations over the conditions of technological partnerships (Brouwer and Kleinknecht, 1999). Therefore it can be ar-

gued that firms that cooperate patent more since they are more innovative (H6-4).
Since patenting is generally associated with R&D activity (Hall et. al. 2012) firms with a higher scientific orientation should also patent more. Therefore, it is hypothesized that: Firms conducting science-oriented R&D are more active in patenting with regard to the number of patents applied for (H6-5). The empirical analysis in this paper tries to test these five hypotheses.

Data and Method

The data used in this paper has been provided by the Thuringian Founder Study. In this study, the main founders 639 start-ups in Thuringia have been interviewed on their social-demographic profile, their psychological factors and on the economic situation of the firm in the year of founding and three years after. After removing some observations due to the fact that they were not genuinely new and due to incomplete data, a population of 534 firms was left for analysis. For these 534 firms, patent information was searched in the database of the German Patent Office. Only 11.98% of the population applied for patents in the time span three years before the firm founding (via their founders) and three years afterward. These 64 firms applied for 633 patents but only 5.46% of them have been applied for in the company's' name. Therefore, the author argued in this paper that an identification of patents for young start-ups is only possible if one is able to search for the founders' name(s) among the applicants.
The outcome variable in this analysis is the number of patents applied for in the first three business years. This variable is highly skewed to the left. However, a zero might have two reasons. First, the firm didn't try to do R&D and apply for a patent and second, the firm was unlucky in its R&D activities and did not come to a patentable result. The author used a zero-inflated negative binomial regression model in order to take care of the fact that the excess zeros can stem from two different processes. The inflation parameter used is R&D activity before firm founding.

Main Results

The results show that there are four main factors that influence small firms' decision to apply for patents. First, the positive influence of patenting experience allows interpreting the results in the light of the success-breeds-success hypothesis (Dosi 1997). Firms whose founders have been successful innovators in the past will be successful in patenting in the future.

Second, start-ups that cooperate are more likely to apply for patents. This goes in line with the arguments of the resource-based view of the firm (Penrose 1959) which stated that there might be resources, especially knowledge, which lie outside the firm and need to be gained by cooperation.

R&D promotion by the State is one further factor which positively influences the firm propensity to patent for start-ups. On the one hand, these firms have more financial scope for the application of a patent, second their innovativeness is already higher in advance since only those firms with a high innovativeness score will receive R&D support (Cantner and Kösters 2009).

The fourth factor which is positively influencing the propensity of a start-up to apply for a patent is scientific orientation. This means, if the firms state that their R&D efforts are scientifically oriented, they apply more for patents.

Contribution

The propensity to patent has been intensively analyzed in the past (see Scherer 1983, Bound et al. 1984, Brouwer and Kleinknecht 1999, Blind et al. 2006, Hall et al. 2012). However, all these studies receive their data from larger company databases which do not catch young and innovative (and very often small) ventures. This paper steps into this gap and analyses the patenting behavior if entrepreneurial ventures.

Since founders of young firms –entrepreneurs- will lose the right to the patent if the firm gets bankrupt, they might not be willing (in the first time) to apply for a patent on the companies' name. Indeed, descriptive statistics have shown that only about 5.5% of the patents applied for by start-ups are applied on the companies' name. Therefore, in contrast to previous studies on patenting activities, this paper votes for taking the founder's patent applications into account when analyzing patent activities of innovative start-ups.

Of course, this study comes with drawbacks which might be solved in the future. First, the chapter only takes Thuringian start-ups into account; second, the strategic reasoning behind patenting could not be analyzed in this study. This leaves open room for future research.

2. Success and failure of firms' innovation cooperations: the role of intermediaries and reciprocity

2.1 Introduction

At least since Schumpeter published his book 'The Theory of Economic Development' (1912), innovations have been seen as the driving force behind economic development. Empirically-founded work by Allen (1983) on blast furnace production, and by von Hippel (1987) on the US mini-mill steel industry, initiated a line of research focusing on actors that cooperate and coordinate their work in order to generate new knowledge and, subsequently, to introduce it via innovations into the market collectively. The motivation for such cooperation based innovative activities is related to a couple of different factors (Bayona et al. 2001). One such factor is the complexity of technological development that often requires several specialized actors and a certain division of labor. Another is that the uncertainty and risk involved in inventive and innovative processes is easier to bear when pooled. In addition, market access is often facilitated by cooperative agreements.

Besides these factors, the uneven spread of knowledge and competencies required to generate new ideas and for these new ideas to result in innovation has also been taken into consideration. As Schumpeter (1912) put it, innovation can be seen as bringing new combinations of resources to the market. Hence, to generate innovations requires recombining existing knowledge (Cantner and Meder 2007). In particular, the appropriate knowledge necessary for successful innovation may not be in the immediate reach of an actor but may rather lie outside (Cowan et al. 2006). Access to such external knowledge may, therefore, be an important prerequisite for innovative success. With these arguments in mind, inventive and innovative activities can be said to rely on processes of collective or social learning and on the exchange of knowledge between actors (Lundvall 1992, Doloreux and Parto 2005).

Despite these presumed advantages of cooperation-based knowledge exchanges, their establishment and continuation face own problems that can affect the generation of new ideas in a significant way. For example, consider a firm with a low level and intensity of cooperation-based exchanges, although there are available enough potential cooperation partners. This may indicate that the firm simply failed to make contact with potential partners, presumably due to a *lack of intermediation*. Another explanation refers to the lack of trust and reciprocity in firms' cooperative relationships, which reduces the incentive to engage in cooperation-based knowledge exchanges, a problem related to the *lack of reciprocity*.[1]

These two problems potentially affecting innovation cooperation are at the heart of this paper. We look at the role they play for the innovative performance of firms.

We proceed as follows. Section 2.2 discusses the theoretical background on which hypotheses are derived. Section 2.3 introduces the data used. Sections 2.4 and 2.5 are devoted to the potential problems of intermediation and of reciprocity. Section 2.6 concludes.

2.2 Theoretical Background

2.2.1 Innovation and Cooperation at the Firm Level

As Chris Freeman (1987, p. 266) said: "… not to innovate is to die." This is the general situation which firms face in today's economic world. Freeman's phrase nicely describes the core of the theory of evolutionary economics, which sees economic change as the result of the emergence and diffusion of innovations (Pyka 1999). Consider a population of actors, different in their ideas and in their behaviors, where some of the individuals begin to search for new and better opportunities and ways to break trough the existing barriers. These individuals are so called "creative entrepreneurs" who, by implementing an innovation and bringing it to the market, create a technological gap (Dosi 1988). The process of creative destruction compels incumbent firms to hold pace with new technological developments and thus to be innovative. The most important ingredient of an innovation is new technological knowledge,

[1] As a third problem, the issue of complementarity of the potentially cooperating partners in terms of knowledge, experience and capabilities is frequently discussed. The low intensity of cooperation-based exchange can also indicate that the knowledge bases of the actors do not fit, i.e. the *lack of compatibility*. With the data used in this paper, lacking information on the actors' knowledge, experience and capabilities, an appropriate analysis cannot be performed. For a respective investigation on the basis of patent data for Germany, see Cantner and Meder (2007).

which may not be completely appropriable to a firm because some of its parts are tacit (Thornhill 2005). The ability of a firm to understand and to exploit such new technological knowledge, respective the absorptive capacity, determines a firm's ability to innovate as well as to imitate (Cohen and Levinthal 1990).

However, innovative activities do not come without constraints for a single firm, which may be abolished by cooperative agreements. First, uncertainty and risk involved in inventive and innovative processes is easier to bear when pooled (Baum et al. 2000, Bayona et al. 2001). Second, the generation of innovations is a process of recombining existing knowledge (Cantner and Meder 2007), since it can be defined as a social process of interactive learning, which occurs through cooperation and interaction between firms and the actors in their environment (Lundvall 1992). The knowledge necessary to innovate successfully, however, may lie outside the firm's boundaries, which may make the access to external knowledge crucial (Cowan et al. 2006). These arguments point to the resource-based-view of the firm, which sees access to productive resources, here mainly technological knowledge, of the partners as main incentive to engage in research cooperation (Penrose 1959). Penrose treats firms as collections of productive resources that are tied semi permanently to the firm. By combining such productive resources of complementary firms, cooperation may enhance the propensity of a successful development project (Teece 1986, Nooteboom 1999). Additionally, the internalization of knowledge spillovers may be another reason to engage in R&D collaboration (Griliches 1992). Following these considerations, firms do not usually innovate in isolation but in collaboration and interaction with other organizations (Fagerberg 2005). These other organizations may be other firms, universities, schools or ministries, the behaviors of which are shaped by institutions (Edquist 2005). Organizations and institutions are components of systems for the generation and diffusion of innovations, namely the systems of innovation (Edquist 2005). The theory of systems of innovation claims that special combinations of organizations and institutions can enhance a firm's ability to innovate and to compete successfully (Cantner et al. 2003).

2.2.2 Problems of Intermediation and Reciprocity in Cooperation

Having described the relationship between innovation and cooperation at the firm level, in the following we will discuss failures that prevent the emergence and the functioning of cooperative projects. The arguments we put forward are based on the assumption that organizations are usually willing to transfer and to exchange knowledge. For that to take place, they have to know where possible partners are or where to search for them; furthermore, for relationships to be sustainable, they have to be reciprocal in the sense that the transfer of knowledge is not one way. Failures with respect to cooperative projects show up if one or both of these two conditions fail. Firms then face a lack of intermediation and/or a lack of reciprocity in (potential) cooperation partners.

Lack of intermediation

To understand the lack of intermediation, it is useful to take a look at the asymmetrically informed borrowers and lenders in financial markets. Seeking information about a potential finance partner causes high transaction costs for firms and private households (Williamson 1986). This can force the actors on the financial market to put up with the high costs, to make contracts without information, or to omit financial transactions (Diamond 1984). Financial intermediation, e.g. by a bank, can bear a net cost advantage in comparison to the direct financing.

The lack of intermediation is just similar. Searching for an appropriate collaboration partner may cause high transaction costs related to gathering information about the existence of potential partners, their knowledge features and their reputations. Firms may be aware of those costs or, more reasonably, they may anticipate but not exactly know their levels. In both cases, if these costs are high or uncertain, actors may be reluctant and refrain from searching for potential cooperation partners.

To overcome this is just the function of intermediaries. The emergence or setting up and partly also the continuation of knowledge exchange between cooperation partners may require an initiator and/or mediator. Those entities are subsumed under the notion of intermediaries. Following Cantner and Graf (2003), among the intermediaries in this sense are offices devoted to technology transfer, public agencies (regional politicians, business development agencies), conferences and know-how markets, collaborative research ventures, patents, other sources of information such as consultants and scientific journals, as well as employees' mobility. Their principle function is to mediate contacts and to transfer knowledge between actors (Karlsson 1997). Obviously, the intermediaries mentioned are different in their abilities to fulfill both of these tasks. Some of them are deliberately installed and formal; others seem to work unconsciously and on a more informal basis. For the purpose of this paper, we look at public agencies, in fact at 'chambers of commerce and industry' and 'business promotion entities', as they act as mediators between regional actors (von Malmborg 2007). For realizing this function, their role could be that of a "teacher" or a "tutor". As to the former, the initiation and continuation of cooperation projects relies on the knowledge and ideas held by the intermediary. Acting as a 'tutor', the intermediary's central position between the actors is not based on an ability to hold, to generate and to diffuse knowledge, but rather consists in enabling actors to make contact with other actors holding the knowledge searched for and required. By looking at the above mentioned public agencies, we here concentrate on intermediaries who act rather as a tutor than as a teacher. Consequently, a lack of intermediation arises when knowledge exchanges among actors do not take place at all or only on a rather low level of success (Cantner 2000). Since 'chambers of commerce and industry' and 'business promotion entities' act as mediators between regional actors, problems with respect to a lack of intermediation automatically comprehend a regional dimension. This, however, will not be the main focus of this paper.

The presumed difficulties in intermediaries' work show two dimensions. First, one task of intermediaries is to arrange cooperation partners for organizations that are willing to cooperate, but as yet have not found the appropriate partner by themselves. This requires firms, when in need of a cooperation partner, to approach an intermediary and to express this need. Firms will only do this if they are aware of intermediaries offering such a service and if they consider the services offered important for the solution of their problems. Thus, whether actors find an appropriate cooperation partner is a function of the alleged importance of intermediate actors. This leads to our first hypothesis:

Hypothesis 2-1:
A comparably higher perceived importance of intermediaries fosters the initiation of collaborative R&D projects.

The second dimension refers to the quality of intermediaries' services and relates it to the success of cooperation. The intermediaries' ability to connect actors in a most fitting way reflects their quality. In the case of a low fitting, collaboration is more likely to fail. Thus, the success of collaboration can be seen as a function of the quality of intermediaries' services. This leads to our second hypothesis:

Hypothesis 2-2:
A higher perceived quality of the intermediaries' services fosters comparably more successful collaborative R&D projects.

<u>Lack of reciprocity</u>
Güth et al. (2002) consider the German proverb "Wie Du mir, so ich Dir!" ("Tit for tat") [p.6] a suitable signpost to understand what reciprocity means for social interaction. It can be defined as the inner tendency of individuals to answer to benevolent or to harming behavior in the same sense (Gouldner 1960, Güth and Yaari 1992, Cialdini and Trost 1998). Reciprocity is the reaction, the answer, to the behavior of others. Consequently, they react friendly and nice to friendly actions and they are nasty and even brutal in reaction to hostile actions (Fehr and Gächter 2000). These principles can be applied to collective invention and innovation. There, cooperative activity in R&D, as one routine to develop new products or processes, "is based on proven past performance and reliability of a cooperative relation, and thus has a rational basis even though it is no longer based on conscious deliberation" (Nooteboom 1999, p.797f.). Hence, reciprocity relies heavily on the reliability and trust among cooperation partners.
Lacking reciprocity causes considerable problems for R&D cooperation; it may even cause no cooperation to occur. Reciprocity in this context means that the transmission of knowledge by one actor is reciprocated by the other actor - not

necessarily *uno actu*[2]. Fehr and Gächter (2000) describe cooperation as reciprocal because the partners have to open their own knowledge stock to get, simultaneously, access to the knowledge stock of the partner. Hence, cooperation partners are required to have mutual incentives (Cantner and Meder 2007). In the case where reciprocity is not given, the exchange of knowledge will not take place. In principle, this can be related to a lack of trust on the level of bilateral relationships, as well as on the system's level.

Accordingly, two types of reciprocity problems can be distinguished. The first type is an ex-ante lack of reciprocity, where the actors are not cooperating because they have prejudices toward the potential partners. In this case, the actors are doubtful about bi- or multilateral know-how streams (Cantner 2000). In order to avoid the danger of opening the own knowledge stock without receiving an appropriate part of the partner's knowledge, actors attempt to go without networking. Hence, because of a lack of trust in a potential partner's reciprocation, knowledge exchange relations will not be taken up[3].

The second type of reciprocity problems is an ex-post lack of reciprocity, which arises from tensions between current cooperation partners. These tensions may be related to one partner free-riding on the others' knowledge stock[4]. Thus, the cheated partner will react by withholding his knowledge stock or by breaking off the cooperation. Hence, if trust is not reinforced or if it is disappointed, actors are not willing to collaborate further (Cantner and Graf 2003). This discussion allows us to formulate the third hypothesis:

Hypothesis 2-3:
The less trust collaborative firms have to their partners, the higher the probability that cooperation will fail.

[2] Reciprocity by no means requires exchange in equal quantities or equally valuable "quantities" of knowledge – for the reason that objective values for the "quantities" do not exist.
[3] With the data at hand, we cannot test this relationship empirically.
[4] Here, it can also be the case that one partner only has the feeling that the other is free riding on his knowledge.

2.3 Data

Data Base and Variables

The data we use are drawn from a questionnaire-based company survey in 2006 which was embedded in the research project "Second Order Innovations" financed by the Volkswagen Foundation. The survey was based on a basic population of 1,793 firms in Northern Hesse, 953 firms in Jena and 365 firms in Sophia Antipolis – all taken from the trade registers. The sectors covered are manufacturing, ICT and research services; the minimum firms size is four employees. For Sophia Antipolis compared to the two other regions, there is a focus on firms mainly from ICT and a few from the pharmaceutical industry. Firms were asked about development, R&D effort, innovative and economic success, as well as cooperative behavior for the period 2003-2006. The response rate was higher than 20% (Northern Hesse 29.5%, Jena 24% and Sophia Antipolis 15%), leading to 832 firms, whereof 529 are located in Northern Hesse, 248 in Jena and 55 in Sophia Antipolis . The sample is representative with respect to industries and to size classes. Table 2-1 describes the variables and table 2-2 shows the correlation matrix.

The core dependent variables in our analyses account for cooperative activities of firms. The binary variable *Coop* indicates whether innovative firms also do R&D in cooperation, with 1 if so and 0 otherwise. The cooperation success is represented by *Coop-suc*, a binary variable, indicating with 1 that cooperation has led to an innovation and 0 otherwise. Cooperation failure is accounted for by *Coop-fai, a* binary variable which takes the value of 1 if the cooperation failed and 0 otherwise.

Indicators for intermediation and trust serve as both dependent and independent variables. The perceived importance of intermediaries' services is measured by the binary variable *Int-imp*, which is the answer to the question: *Are the location factors 'chambers of commerce and industry' and 'business promotion entities' important for the innovative activities of your firm?* The variable *Int-imp* takes a value of 1 if the firm replies with 'yes', and 0 otherwise. Besides the evaluation of the importance of intermediaries, firms were asked to evaluate intermediaries' quality on a 5-digit-Likert-scale, with higher values indicating better evaluations. The variable *Int-qua* accounts for this quality dimension. The variable *Ex-post-trust* is constructed from three 5-digit-Likert scales on trust to regional, national and international cooperation partners. The question we asked is: *How would you evaluate the mutual trust to your regional, national or international cooperation partners?* A higher value of *Ex-post-trust* indicates a higher level of trust.

In order to account for a range of other determinants of interest, we use control variables with respect to the cooperation structure of the firms considered. The binary variables *Coopsc, Coopco,* and *coopers* indicate whether cooperative firms worked together with suppliers/customers (*Coopsc*), competitors (*Coopco*) and/or research institutes (*Coopres*). Binary control variable *Group* indicates whether the respondent firm belongs to a firm group. A firm's share of high-educated employees in total employees is accounted for by *Edu-r*. The variable *Age* measures the firms' age in years in 2006, when the questionnaire was conducted. The variable *Size* measures the firm size as the natural logarithm of the number of employees. Finally, several dummies indicating the firms' industry by two-digit NACE codes are used.

For the sake of taking into account regional specific effects, we use dummy variables indicating whether a firm belongs to the region of Jena (*Je*), Northern Hesse (*Nh*) od Sophia Antipolis (*Sa*). As to correlations among the independent variables in table 2-2, we find if at all only low indications.

Table 2-1 Variables used for analyzing the role of intermediaries and reciprocity for innovation cooperation

Use	Variable	Description	Obs.	Mean	Std. Dev.	Min	Max
Dependent variable	*Coop*	Binary variable with a value of 1 if this firm engaged in cooperation within the last three years and 0 otherwise.	829	0.448	0.498	0	1
	Coop-suc	Binary variable with a value of 1 if this firm has successfully developed a new product or process with a cooperation partner within the last 3 years and 0 otherwise.	827	0.244	0.430	0	1
	Coop-fai	Binary variable with a value of 1 if this firm engaged in cooperation within the last three years and this cooperation failed. Otherwise this value is 0.	827	0.036	0.187	0	1
H2-1	*Int-imp*	Binary variable with a value of 1 if this firm claimed that regional intermediate actors are important for the firm development and 0 otherwise.	764	0.191	0.393	0	1
H2-2	*Int-qua*	The firms were asked to evaluate the quality of regional intermediate actors on a 5-digit-Likert-scale. The higher the value, the better the quality.	489	2.679	1.070	1	5
H2-3	*Ex-post-trust*	Average value from a 5-digit-Likert-scale on trust to regional, national and international cooperation partners. The higher the value the higher the trust to partners.	318	3.854	0.702	1	5

Table 2-1 continued

Use	Variable	Description	Obs.	Mean	Std. Dev.	Min	Max
Controls	*Je*	Regional dummy with a value of 1 if this firm is located in Jena and 0 otherwise.	832	0.298	0.458	0	1
	Nh	Regional dummy with a value of 1 if this firm is located in Northern Hesse and 0 otherwise.	832	0.636	0.481	0	1
	Sa	Regional dummy with a value of 1 if this firm is located in Sophia Antipolis and 0 otherwise.	832	0.066	0.249	0	1
	Coopsc	Binary variable, indicating whether cooperation partners are stemming from the firm's supply chain (customers and suppliers).	436	0.456	0.499	0	1
	Coopco	Binary variable, indicating whether cooperation partners are competitors of the respective firm.	437	0192	0.394	0	1
	Coopres	Binary variable, indicating whether cooperation partners are research institutes.	437	0.279	0.449	0	1
	Group	Binary variable with a value of 1 if this firm is a member of a firm group and 0 otherwise.	826	0.229	0.420	0	1
	Edu-r	Share of high-educated employees in total employees.	733	0.289	0.324	0	1
	Age	Firm age, measured in years.	816	28.366	39.669	1	606
	Size	Firm size, measured in natural logarithm of the number of employees.	820	2.801	1.465	0	8.846
	Industry	Several dummies were included for two-digit industry codes (NACE).					

Table 2-2 Correlation matrix of variables used for analyzing the role of intermediaries and reciprocity for innovation cooperation

		1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*
1	*Size*	1									
2	*Age*	0.2275	1								
3	*Group*	0.3650	-0.0323	1							
4	*Edu-r*	-0.2561	-0.2491	0.1343	1						
5	*Coop*	0.1734	-0.0604	0.2687	0.2203	1					
6	*Coop-suc*	0.1899	-0.0565	0.1985	0.2164	0.6334	1				
7	*Coop-fai*	0.0940	-0.0400	0.1249	0.0270	0.2161	0.1004	1			
8	*Int-imp*	0.0148	-0.0402	-0.0506	0.0127	0.0485	0.1197	0.0554	1		
9	*Int-qua*	0.0500	-0.0177	0.0420	0.0759	0.0004	0.0383	0.0419	0.1460	1	
10	*Ex-post-trust*	-0.0229	-0.0857	0.1087	0.2438	.	0.1374	-0.0580	0.0989	0.0568	1
11	*Coopsc*	0.2429	0.0615	0.1402	0.0686	0.5537	0.3690	0.1111	-0.0236	-0.0239	-0.0646
12	*Coopco*	0.1520	0.1224	0.0042	0.0058	0.2941	0.0927	0.0978	-0.0718	-0.1111	-0.0707
13	*Coopres*	0.2751	0.0122	0.2177	0.1947	0.3753	0.3443	0.0217	0.0345	0.0285	0.1615

Table 2-2 continued

		11	*12*	*13*
11	*Coopsc*	1		
12	*Coopco*	0.1378	1	
13	*Coopres*	0.3679	0.0778	1

First Descriptives

Table 2-3 gives an overview on the structure of the empirical basis with respect to innovation and cooperation. We find that 73.20% of the firms in our database report conducting innovative activities. A glance at the percentage of those innovative firms which have been successful reveals that 61.41% of all innovative firms brought their innovative activities to a success, namely to an innovation. Looking additionally at R&D cooperation, we find 50.90% of the responding firms report being cooperative, whereof 65.16% succeed with a marketable innovation.

Table 2-3 Describing the database for the analysis of success and failure in innovation cooperation

Number of firms	**832**
Innovators	**609**
In % of all firms	73.20
Successful innovators	**374**
In % of innovative firms	61.41
Cooperators	**310**
In % of innovative firms	50.90
Successful cooperators	**202**
In % of cooperative firms	65.16
Unsuccessful cooperators	**30**
In % of cooperative firms	9.68

2.4 Empirical investigation

2.4.1 Lack of Intermediation

The first problem analyzed is the role of intermediaries, whose task it is to get suitable actors into contact. For being successful herein, the existence of intermediaries has to be considered important or necessary, because, otherwise, actors would not consider preoccupying their services. Additionally, the service of the intermediate actors has to be of good quality. We test for both conditions and suggest an intermediation problem to exist if there is a low propensity to cooperate, combined with a low perceived importance, and/or if there is a low propensity to cooperate successfully, combined with a low perceived quality of the intermediate actors' services.

As stated in section 2.2, technology transfer offices, public agencies, patents, conferences etc. may take the role of an intermediary. For our analysis, we concentrate on public agencies, in particular on the role of 'chambers of commerce and industry' and of 'business promotion entities'.

2.4.1.1 Importance of Intermediaries

As a first step, we test whether the perceived importance of the intermediate actors has an influence on the actors' probability of being engaged in cooperative R&D projects. We here restrict our sample to innovative firms and, due to the binary nature of *Int-imp,* run logit regression models on the variable *Coop*. If intermediaries just fulfill their assumed role as initiators, the variable *Int-imp* should have a positive coefficient, thus increasing the cooperation probability. Our results are presented in table 2-4, where the models are distinguished by the separate inclusion of independent variables.

We find neither a significant effect of the variable *Int-imp* nor of the region specific variables *Int-imp**Sa*, *Int-imp**Je*, *Int-imp**Nh* on the cooperation probability. Thus, we conclude that, at least for our data, no direct effect of the perceived importance of intermediate actors on the cooperation propensity shows up. Hence, we reject hypothesis 2-1.

The coefficients of control variables indicate that being member of a firm group and employing a larger share of higher-educated persons are related to a higher probability to cooperate. These results contribute to former empirical studies on cooperation propensity which find membership in a firm group (Baum et al. 2000), and the internal education level, indicating firm's absorptive capacities (Cohen and Levinthal 1990), to influence positively the cooperation propensity.

Table 2-4 Influence of intermediaries' importance on cooperation

Method	Logit regression						
Dep. Var.	*Coop*						
Population	innovative firms						
	model 1	model 2		model 3		model 4	
Int-imp	0.307	0.243		0.238			
	(1.43)	(0.90)		(0.88)			
*Int-imp * Sa*						0.700	
						(0.73)	
*Int-imp * Je*						0.150	
						(0.27)	
*Int-imp * Nh*						0.212	
						(0.65)	
Je				0.223		0.239	
				(0.71)		(0.71)	
Sa				-20.274		-20.258	
				(-15.09)	***	(-12.93)	***
Size		0.037		0.047		0.046	
		(0.43)		(0.55)		(0.54)	
Age		-0.000		0.000		0.000	
		(-0.12)		(0.04)		(0.04)	
Group		1.087		1.107		1.112	
		(4.11)	***	(4.14)	***	(4.15)	***
Edu-r		1.247		1.175		1.159	
		(2.94)	***	(2.66)	***	(2.61)	***
Industry		yes		yes		yes	
Intercept	-0.008	-0.896		19.391		19.291	
	(-0.09)	(-1.65)	*	(14.39)	***	(12.90)	***
No. of Obs. [a]	592	487		487		487	
Mc Fadden Pseudo R^2	0.0025	0.1175		0.1241		0.1245	

Robust z statistics in parentheses
*, **, *** indicates significance at the 10%, 5% level, 1% levels respectively.

Besides these two main factors, the dummy for firms located in Sophia Antipolis is negatively significant, indicating that these firms are less likely to cooperate compared to the firms from the other two regions. Firm size, as well as age, do not show significant coefficients.

Since we could not find a direct effect of intermediaries' importance on the likelihood to cooperate per se, we restrict our analysis to cooperative actors and test whether the perceived importance of intermediaries has an influence on cooperative success. We use the same model specification as before and run logit regressions on the effect of the importance of 'chambers of commerce and industry' and 'business promotion agencies' on the success of collaboration projects. Table 2-5 shows the results.

Looking first at the control variables, we find a positive relation to cooperation with research institutes, whereas we cannot find significant relations to cooperation along the supply chain, namely with suppliers and customers, or with competitors. Moreover, the size is positively related to the successful completion of cooperative projects, whereas a firm's age shows a negative relation.

The importance of intermediaries on cooperation success is analyzed in models 2 and 3 of table 2-5. Our analysis shows a significantly positive coefficient of the *Int-imp* in model 2, indicating that firms that consider intermediaries' work as important tend to be more successful in cooperating. In order to find out which of the regions may be responsible for this finding, we additionally regressed region specific coefficients of *Int-imp* in model 3. The regional coefficient of the perceived importance of intermediaries on cooperation success is positively significant only for Northern Hesse, whereas the coefficient for Jena is not significant. Thus, the perceived importance of intermediary actors correlates with the success probability of cooperation in R&D, but not everywhere.

Taking the results of table 2-5, we find that those actors that recognize the importance or the worthiness of intermediaries' services tend to cooperate more successfully. However, this effect seems to be driven by actors located in Northern Hesse, which points to regional specificities of this issue.

Table 2-5 Influence of intermediaries' importance on cooperation success

Method	Logit regression					
Dep. Var.	*Coop-suc*					
Population	Cooperative firms (*Coop* = 1)					
	model 1		model 2		model 3	
Int-imp			1.103			
			(2.56)	***		
*Int-imp * Je*					0.275	
					(0.47)	
*Int-imp * Nh*					1.546	***
					(2.90)	
*Int-imp * Sa*[a]					dropped	
Size	0.237	*	0.418	***	0.424	***
	(1.88)		(2.84)		(2.85)	
Age	-0.007		-0.012		-0.014	
	(-1.27)		(-2.00)	***	(-2.22)	**
Group	0.031		0.137		0.184	
	(0.10)		(0.40)		(0.54)	
Edu-r	0.448		0.317		0.518	
	(0.75)		(0.50)		(0.79)	
Coopsc	0.270		0.485		0.447	
	(0.89)		(1.48)		(1.36)	
Coopco	-0.143		-0.260		-0.240	
	(-0.44)		(-0.73)		(-0.67)	
Coopres	0.614	*	0.789	**	0.825	**
	(1.88)		(2.15)		(2.24)	
Industry	yes		yes		yes	
Intercept	-0.747		-0.075		0.041	
	(-0.49)		(-0.05)		(0.03)	
No. of Obs. [b]	267		242		242	
Mc Fadden Pseudo R^2	0.0996		0.1507		0.1587	

Robust z statistics in parentheses
*, **, *** indicates significance at the 10%, 5% level, 1% levels respectively.
[a] Note that *Int-imp * Sa* was dropped due to collinearity.

2.4.1.2 Quality of intermediaries

As a second step in analyzing intermediation problems, we look at the quality of intermediaries as evaluated by the firms. We first attempt to determine firm specific differences in the quality evaluation. Since Likert-scale-type dependent variables require running ordered logistic regressions, we regress our firm specific control variables on the perceived quality (*Int-qua*) using OLogit[5]. The results are presented in table 2-6. We run two models, where the first accounts for the control variables only. Model 1 in table 2-6 shows that all control variables, except *Edu-r*, show no significant influence on the evaluation of intermediaries at all. Thus, a higher share of high-educated employees increases the quality evaluation of the firms. Model 2 provides an additional analysis by looking at the relation of the perceived importance of intermediate actors to their perceived quality. Our analysis of intermediaries reveals a relationship between the perceived importance of intermediaries and cooperation success, which in this step of analysis is the variable of interest. We find that firms claiming regional intermediaries to be important tend also to give a better evaluation for these actors. This finding strengthens our intuition in combining both steps of analysis (relationship between *Int-qua* and *Int-imp*). The awareness of the use of intermediaries' services seems to have a positive influence on the perceived quality of these services.

From the results in model 3 of table 2-5, we have already seen an indication of this point, where we find that those actors who recognize the importance or the worthiness of intermediaries' services tend to cooperate more successfully. This effect, however, is specific to firms located in Northern Hesse, implying that the intermediation of contacts in this region seems to be successful, but most firms in this region do not recognize that. Therefore, presumably the major problem for intermediating suitable partners is rather a communication than a programmatic problem. Intermediaries have to communicate what they can do for firms and the worthiness of the mediation of suitable partners. If they can communicate this, the quality of their work may not have such a big influence because actors then automatically feel confident about the service. With respect to our theoretical considerations, we conclude that the perceived importance, rather than the perceived quality, of intermediaries in a region may be the key for more successful cooperation. In other words, firms have to recognize what intermediaries can do for them, if they seek successful cooperation.

[5] Here the actual values taken on by the dependent variable are irrelevant, except that larger values are assumed to correspond to "higher" outcomes. This is due to the fact that this evaluation method has clear cut definitions for each scale.

Table 2-6 Firm specific differences in quality evaluation

Method	Ordered logistic regres-			
Dep. Var.	*Int-qua*			
Population	all firms			
	model 1		model 2	
Int-imp			0.799	
			(3.59)	***
Size	0.092		0.101	
	(1.14)		(1.24)	
Age	-0.001		-0.001	
	(-0.27)		(-0.27)	
Group	-0.189		-0.133	
	(-0.79)		(-0.55)	
Edu-r	0.735		0.683	
	(1.86)	*	(1.72)	*
Industry	yes		Yes	
No. of Obs. [a]	427		424	
McFadden Pseudo R^2	0.0285		0.0417	

Robust z statistics in parentheses
*, **, *** indicates significance at the 10%, 5% level, 1% levels respectively.
[a] Note that the number of observations changes between the models since there are missing observations for some variables.

In a further step, we test whether the perceived quality of intermediaries' services is positively correlated to the binary variable *Coop-suc*. Table 2-7 contains the estimation results.
For models 1 to 3, looking at the relation of the overall *Int-qua* to the cooperation success probability, no significant coefficients are estimated. This leads us to reject hypothesis 2-2. Also in model 4, attempting to find region specific relations between the intermediaries' quality and cooperation success, no significant coefficients are found. With respect to the controls, *Size* has a significantly positive coefficient, whereas *Age* shows a (weakly) significant negative relation to cooperative success.

Summarizing this section, we neither identify a direct effect of the perceived importance of intermediaries' services on cooperation, nor do we find a direct relationship between the perceived quality of intermediaries' services and cooperation success. However, we identify an indirect effect which may lead us to identify a failure in Northern Hesse. Looking only at cooperative firms, we find that firms that perceive intermediaries important state also a successful cooperation. This result is mainly driven by firms located in Northern Hesse. Of course, this cannot be taken as a causal relationship and it may equally hold true that only those who had cooperation success then ex-post consider intermediaries important. Nevertheless, the failure in Northern Hesse may lie in the misjudgement of intermediaries' worthiness. If an actor in Northern Hesse, however, understands intermediaries' services as important, then he usually cooperates more successfully.

Table 2-7 Influence of intermediaries' quality on cooperation success

Method	Logistic regression						
Dep. Var.	*Coop-suc*						
Population	Cooperative firms						
	model 1	model 2		model 3		model 4	
Int-qua	0.147	0.271		0.269			
	(1.12)	(1.39)		(1.37)			
*Int-qua * Sa*[a]						dropped	
*Int-qua * Je*						0.605	
						(1.43)	
*Int-qua * Nh*						0.168	
						(0.75)	
Je				0.110		-1.177	
				(0.18)		(-0.77)	
Sa[a]				dropped		dropped	
Size		0.606		0.613		0.601	
		(2.88)	***	(2.86)	***	(2.81)	***
Age		-0.015		-0.015		-0.015	
		(-1.84)	*	(-1.77)	*	(-1.76)	*
Group		0.329		0.313		0.313	
		(0.70)		(0.66)		(0.65)	
Edu-r		0.726		0.672		0.752	
		(0.81)		(0.71)		(0.80)	
Coopsc		0.494		0.490		0.540	
		(1.15)		(1.14)		(1.24)	
Coopco		-0.261		-0.264		-0.240	
		(-0.58)		(-0.58)		(-0.53)	
Coopres		-0.009		-0.020		0.029	
		(-0.02)		(-0.04)		(-0.06)	
Industry		yes		yes		yes	
Intercept	-0.189	-1.502		-1.509		-1.360	
	(-0.51)	(-0.95)		(-0.96)		(-0.86)	
No. of Obs. [b]	227	158		158		158	
Mc Fadden Pseudo R^2	0.0041	0.0480		0.1806		0.1846	

Robust z statistics in parentheses

*, **, *** indicates significance at the 10%, 5% level, 1% levels respectively.

[a] Note that *int-qua * Sa* and *Sa* were dropped due to collinearity.

2.4.2 Lack of Reciprocity

Our next step is concerned with the issue of reciprocity governing the cooperative activities of firms. We operationalize reciprocity with the firms' evaluation of the trust they have in current cooperation partners. We decided to ask firms for an evaluation of trust, instead of reciprocity, because trust is a more common concept which is easier to evaluate for individuals. Moreover, trust between cooperation partners who are usually market oriented firms is very likely to be the result of reciprocity. Without reciprocity, no cooperation would occur because of the danger of free riding. If actors get in touch and cooperate for a while, what they 'feel' and can evaluate is more related to trust than to reciprocity. Therefore, it should make sense to ask for trust rather than for reciprocity.

In our analysis, we investigate whether the failure of cooperative ventures is related to missing trust towards partners involved herein. This relation points to an ex-post lack of reciprocity.

We first use cooperation success as a dependent variable, represented by the binary variable *Coop-fai* which takes the value of 1 if the cooperation failed. The core independent variable we use here is the ex-post reciprocity variable *Ex-post-trust*. In addition, we use region specific *Ex-post-trust* variables, *Ex-post-trust*Nh*, *Ex-post-trust*Sa*, *Ex-post-trust*Je*, as well as the control variables *Size*, *Age*, *Group, Edu-r, Coopsc, Coopco* and *Coopres*. The logit regression results on *Coop-fai* are presented in table 2-8. Model 1 looks only at the control variables and finds that breaking off of cooperative projects without finding an innovation is negatively related to cooperating with research institutes. Thus, fewer cooperative projects are broken off if the cooperation partner is a research institute.

In model 2, we test for the impact of trust in general. The variable *Ex-post-trust* shows a significantly negative coefficient, indicating that a higher level of trust is related to a lower probability of failure, which supports our hypothesis 2-3. To account for regional differences, in model 3 we include region specific trust variables.

Table 2-8 Influence of trust on cooperation failure

Method	Logistic regression					
Dep. Var.	*Coop-fai*					
Population	cooperative firms					
	model 1		model 2		model 3	
Ex-post-trust			-4.029	**		
			(-2.14)			
*Ex-post-trust * Je*					-3.983	**
					(-2.11)	
*Ex-post-trust * Nh*					-4.117	**
					(-2.14)	
*Ex-post-trust * Sa*[a]						
Size	0.395		-1.204		-1.255	
	(1.30)		(-1.25)		(-1.28)	
Age	-0.009		-0.100	*	-0.100	
	(-0.64)		(-1.76)		(-1.79)	
Group	0.663		3.084		3.175	
	(0.90)		(1.47)		(1.48)	
Edu-r	-0.949		-1.130		-1.345	
	(-0.71)		(-0.39)		(-0.44)	
Coopsc	0.156		-2.691		-2.831	
	(0.22)		(-1.08)		(-1.10)	
Coopco	0.163		-0.956		-0.904	
	(0.24)		(-0.44)		(-0.45)	
Coopres[a]	-1.525	*				
	(-1.85)					
Industry	yes		yes		yes	
Intercept	-0.940		16.704	*	24.572	**
	(-0.56)		(1.88)		(2.18)	
No. of Obs.[b]	144		49		61	
Mc Fadden Pseudo R^2	0.1741		0.4989		0.5004	

Robust z statistics in parentheses
*, **, *** indicates significance at the 10%, 5% level, 1% levels respectively.
[a] Note that *Ex-post-trust * Sa* as well as *Coopres* was dropped due to collinearity.

For Jena and Northern Hesse, we find significant coefficients, where the one for Northern Hesse is larger. We take this as an indication that trust and reciprocity play a larger role in Northern Hesse compared to Jena. The reasons for that require further scrutiny by taking into account region's specificities in future work.

2.4.3 Conclusions

In this paper, we looked at the relation between cooperation propensity and cooperation success of firms, on the one hand, and the perceived problems of intermediation and reciprocity on the other. In particular, we attempted to answer the following question: Is the likelihood to be engaged in cooperative innovation related to the perceived importance and quality of intermediaries? Can we provide evidence for differences in cooperative innovative success between firms, stemming from a lack of intermediation and of reciprocity? In order to answer these questions, we analyzed firm questionnaire data for the three regions, Northern Hesse and Jena in Germany, and Sophia Antipolis in France. On the basis of four hypotheses, we tested the influence of a lack of intermediation and of reciprocity on cooperative innovation.

As to our results, first, we had to reject our hypotheses 2-1 and 2-2 related to the importance and quality of intermediaries: The lack of intermediation is not related to a higher likelihood of cooperative behavior as such (hypothesis 2-1), and the quality of intermediation is not related to cooperation success (hypothesis 2-2). However, we found that, among the cooperative firms, the importance of intermediaries is positively related to cooperation success. In addition, we found regional differences: First, in Sophia Antipolis the likelihood to cooperate in innovation seems to be much lower, which is surprising because this site was constructed by political will in order to enhance cooperation. Second, for Northern Hesse, the relation of intermediaries' importance on cooperative success appears to be much stronger, suggesting that the major problem for intermediation actors is communication rather than programmatic work. Both issues ask for further scrutiny by taking into account the characteristics of the respective region, the innovation system and/or the network of innovators.

Second, as to the problem of reciprocity in knowledge exchange, we found that actors tend to break off cooperative projects because of missing trust to the cooperation partners, which supports our third hypothesis.

Drawing some policy implications from these results, we propose that local intermediary organizations in Northern Hesse should check for the visibility of their activities if they observe a lack of demand for their services from firms. Missing trust seems to be a driver of discontinued research cooperation. However, trust may also be related to the definition of agreements and contracts. In line with making contacts between the actors, regional intermediaries may provide advice with respect to cooperative agreements.

Despite the fact that we were able to identify a lack of reciprocity as a driver of differences in collaborative-innovation success and that Northern Hesse seems to be coined by a systematic failure with respect to its intermediaries' work, some limitations of the analysis have to be mentioned. First, the number of returns of the questionnaire differed much among the regions. We compared Northern Hesse – 529 answers – with Jena – 248 answers – and with Sophia Antipolis – 55 answers. Second, besides a lack of intermediation and of reciprocity, there may be a third problem, crucial to the success of collaborative innovation, the lack of compatibility. Due to the limited data base we used, we were not able to test for that. Future research aims on filling this gap. We plan to conduct an analysis aiming at all of the three dimensions of lack.

3. The Coevolution of Innovative Ties, Proximity, and Competencies: Toward a Dynamic Approach to Innovation Cooperation

3.1 Introduction

The growing complexity and shortening of cycles inherent in the innovation process have changed the industrial and technological environment in which firms operate. The associated increase in uncertainty and costs accompanying R&D projects has shaped a landscape that favors collaboration (Hagedoorn 2002). Especially in high-tech industries, where knowledge creation and accumulation is a crucial input factor and competition has become a learning race, joint research has steadily grown since the 1980s (Mowery et al. 1996, Powell 1998).

A basic feature of joint research is the exchange and sharing of knowledge among the cooperation partners. Actors choose research cooperation in the expectation that it will maximize their potential gain in knowledge. In this context several scholars have stressed the importance that similarity between cooperation partners has for knowledge transfer and successful collaboration. Similarity determines with whom one connects, for it creates trust, facilitates knowledge flows, and increases the mutual attractiveness of potential collaboration partners (Boschma 2005, McPherson et al. 2001). Similarity or proximity in three dimensions—cognitive, social, and competence-related—seems to play a cardinal role in knowledge exchange in collaborations intended to generate innovation.

These three dimensions are not simply exogenously given and static; they develop in the course of the partners' collaboration. Continued collaboration leads trust, experience and common understanding to eventually increase, and knowledge differences to decrease. These dynamics are expected to determine whether the same partners always cooperate or whether they switch partners over time. Increasing trust, experience, and common understanding tend to contribute to the continuation of the partnership because they increase the efficiency of knowledge exchange and sharing. Conversely, the declining difference between knowledge stocks of continuously cooperating partners —that is, an increase in their cognitive proximity (the degree of similarity of their knowledge bases)—indicates that opportunities to exchange and share knowledge have been exploited by them and should therefore lead to partner-switching.

Hence, the relation between certain proximity dimensions and continuation of collaboration is by no means unidirectional (Ter Wal and Boschma 2011). In fact, individual characteristics (e.g., technological capabilities), and thus the proximity to others, co-evolve with continuous collaboration (Balland et al. 2015, Ter Wal and Boschma 2011). These dynamics have undergone little empirical analysis (Balland et al. 2015). Although the coevolution of factors driving collaboration choice and the evolution of ties can be explored only with a dynamic approach, most of the studies on the relation between proximity and cooperation have been rather static (e.g., Wuyts et al. 2005, Cantner and Meder 2007, Paier and Scherngell 2011).

In this chapter we want to contribute to the field of dynamic approaches and analyze the interplay between cognitive proximity, knowledge exchange and collaboration. We focus our analysis on ties within innovator networks defined as an ensemble of direct and indirect connections, with the direct ones being research collaborations intended to produce innovations (Cantner and Graf 2006). Tracking the individual actors and their collaborations over time, we pursue the following core research question: To what extent do knowledge dynamics between two cooperating actors determine the continuation of their innovative ties? Accordingly, we concentrate mainly on the dynamics of partners' cognitive proximity; in addition we analyze the other two dimensions, trust and competencies, as further important covariates.

Our descriptive analysis suggests that firms are generally prone to switching their cooperation partner rather than to repeating the collaboration with that partner. We thus find that the knowledge transfer and cooperation that partners have experienced with each other have no significant effect on the likelihood that they will repeat their cooperation. Our empirical analysis also shows that cooperation is promoted by several factors: an overlap between the firms' knowledge bases, an uneven distribution of the reciprocal potential for knowledge exchange, general collaboration experience of the partners, and similarity in the popularity of the collaboration partners. We also find that firms prefer to cooperate with partners that are different in organizational nature and age.

We begin by providing a general overview of basic concepts and principle arguments that describe the relation between similarity in knowledge, experience, and their effect on tie formation. We then characterize how these relations dynamically co-evolve with ongoing collaboration and present our hypotheses. In the second section we explain our methodological approach, including data and variable descriptions. The third section presents the final results and our discussion of them. In the final section we offer suggestions for further research.

3.2 Knowledge Dynamics and the Evolution of Innovation Linkages

3.2.1 The Role of Cognitive Proximity, Social Proximity, and Similarity in Competencies in the Formation of Innovative Ties

The increased orientation to collaboration, especially in research and development (R&D), has led to an upsurge of studies analyzing the advantages and incentives that are encouraging the trend toward the formation of alliances (e.g. Ahuja 2000, Gilsing et al. 2008, Gulati 1999, Hagedoorn 2002, Hamel 1991, Khanna et al. 1998, Mowery et al. 1996, Powell 1998). Essentially, most alliances are prompted by concerns about access to external resources that are too costly to be acquired internally (Kogut et al. 1992). In innovation-oriented alliances the access to a partner's technology and knowledge-related resources—be they a particular technical infrastructure or, more important, technological capabilities and complementary skills—is the primary motive for joint research, besides the sharing of risks and R&D costs (Hagedoorn 2002). Firms, especially those in high-tech industries, are unable to generate internally all the resources they need in order to survive the rapid pace of technological change (Powell and Grodal 2006). According to the knowledge-based view of the firm (which draws on the resource-based view of the firm originally proposed by Penrose (1959)), a firm's knowledge base, understood as a unique resource difficult to imitate, is a key competitive advantage (Grant and Baden-Fuller 1995). In this regard firms can be seen as bundles of competencies (Hamel 1991, p. 83) that they have accumulated throughout their lifespan. Because environments and solutions to problems differ between firms, knowledge gathered by firms is an idiosyncratic property and quite heterogeneous among them

(Cantner and Graf 2011). Even firms operating in the same industry or market differ in what they know and what they are able to accomplish with their competencies. Although this proprietary knowledge resource affords a basis for opportunities, its exploitation within the firm's boundaries is limited and leads mostly to incremental, not necessarily optimal, improvements (Ahuja 2000, March 1991, Yang et al. 2010). To broaden the knowledge base and explore new possibilities for recombination and radical innovations, firms depend on external sources of knowledge (March 1991, Yang et al. 2010). In looking for solutions to complex problems, successful innovators extend their search to the environment beyond their own boundaries (Freeman 1991). The generation of knowledge and innovation thus results progressively from a collective learning process among various actors interacting formally or informally (Asheim and Gertler 2005).

In innovation-oriented alliances rational actors choose their potential interaction partners according to the highest expected outcome in terms of successful knowledge exchange and potential innovations. The efficacy of knowledge exchange between two or more actors is governed by the degree of heterogeneity between them. The proximity approach, proposed originally by Boschma (2005), emphasizes that similarity (conceptually the inverse of heterogeneity) or as he calls it proximity affects the ease of knowledge transfer between actors. He thereby differentiates between various dimensions of proximity whose prominence can differ from one type of alliance to another. In R&D alliances explicitly conceived to generate novel ideas and innovations, cognitive proximity might predominate over other forms of proximity as the basis for potential knowledge flows, and social proximity (also called the strength of social ties between collaborators) might take precedence as the control mechanism for knowledge flows.

Understood as the similarity of knowledge bases, cognitive proximity can determine the degree of knowledge exchange between actors through two central characteristics representing a trade-off in collective learning: mutual understanding and learning potential. Mutual understanding is the degree to which different actors comprehend each other, and it increases with cognitive proximity. Potential partners therefore need to exhibit some minimum degree of cognitive proximity to warrant mutual understanding. Learning potential has to do with the amount of what can be mutually learned, and it decreases with cognitive proximity. The heterogeneity of firms in knowledge space is a source of learning effects because relatively great dissimilarity can increase learning potential and the exchange of knowledge (Nooteboom 2005).

The idea of combining the two dimensions of cognitive proximity—that of being a condition for mutual understanding and that of being a source of knowledge exchange—suggests the existence of an intermediate degree of proximity at which beneficial exchange of knowledge is maximized (Boschma 2005, Gilsing et al. 2008, Nooteboom 1999). A deviation from this level will lead either to increased potential for exchanging knowledge combined with lowered common understanding or to increased common understanding combined with lowered potential for novelty. Consequently, an actor conducting a strategic and rational search for a research partner should, at least theoretically, try to connect with a candidate who are similar in knowledge stocks and partly complement his or her own so as to acquire the potential for creating novelty.

Besides the relevance of an optimal degree of cognitive proximity for understanding and learning, the second condition for effective collaboration to take place is the controllability of the knowledge-exchange-and-sharing relation. It is here that social proximity comes in. Social proximity accounts for familiarity and trust between cooperation partners, two facets that facilitate the transfer of tacit knowledge and reduce the occurrence of opportunistic behavior. Trust affects the efficiency of knowledge transfer as familiar and trusting partners have internalized norms of communication and therefore can better control undesired behavior such as free riding (Granovetter 2005). Hence, the cooperation with trusted partners warrants increased reciprocity for their efforts. Frequently proposed mechanisms for developing social proximity include mobile inventors, who often maintain social relations with their former workplace; the existence of positive experience gained in previous collaboration; familiarity with each other before cooperation; and acquaintance through a common partner (Ter Wal and Boschma 2009). A strategic and rational actor should therefore prefer to link up with actors who are already in his or her circle of acquaintances. In addition to cognitive and social proximity as means to develop social proximity, Boschma (2005) suggested geographic, organizational, and institutional proximity between partners to support learning and innovation. For successful R&D collaboration and the generation of innovations, we assume that social and cognitive proximity outweigh other dimensions of proximity because the creation of new ideas and the generation of innovation is a costly and uncertain process primarily determined by the knowledge involved (Moweryet al. 1998). In focusing on the examination of learning dynamics in R&D collaborations, we concentrate our argumentation on these two relevant dimensions of proximity. The likelihood of collaboration increases with the social proximity and shows an inverted-u relationship with respect to the cognitive proximity of the potential partners.

Recent empirical findings underpin these arguments. Despite the differences in the measurement of the proximity dimensions, the positive effect of social proximity on the probability of collaboration has developed as stylized fact in most of the studies on bilateral collaboration and the factors that explain its establishment and the exchange of knowledge (Ahuja 2000, Broekel and Boschma 2012, Cantner and Meder 2007, Criscuolo et al. 2010, Gulati 1995/ 1999, Gulati and Gargiuolo 1999, Mowery et al. 1998, Paier and Scherngell 2011, Powell 1998, Singh 2005).

The results concerning cognitive proximity are less congruent chiefly due to the difficulty of finding appropriate proxies and the divergence of applied measures. Paier and Scherngell (2011), Cantner and Meder (2007), and Singh (2005) found a purely positive effect of knowledge proximity on tie formation, whereas Criscuolo et al. (2010), Mowery et al. (1998), and Wuyts et al. (2005) gave evidence of the inverted-U relationship between cognitive proximity and the proclivity to cooperate or to share knowledge as originally proposed by Nooteboom (1999). Consistently, Gilsing et al. (2008), and Wuyts et al. (2005), observed also an inverted U-shaped curve for the relation between cognitive proximity and the innovative performance of R&D projects. By contrast, Broekel und Boschma (2012) observed what is called the proximity paradox in their analysis of link formation and link performance in the aviation industry: Although proximity seemed to guide the formation of new R&D alliances, cognitive proximity especially hindered the innovative performance of the observed links.

Scholars have also identified factors that go beyond the link-specific proximity as inducers of opportunities for actors to collaborate. Among them are economic factors (e.g., accumulated capabilities and resources) and the general embeddedness of a firm in its relevant environment (e.g., the industry, the region). Signalling competence to other actors in the network (Ahuja 2000, Stuart

2000), both aspects enhance the perceived attractiveness of actors as a potential collaboration partner. In general, firms relatively well endowed with resources, such as innovative capabilities (past innovation activity) or technical capital (technology stock), can exploit more opportunities to form links than less well-endowed firms, for potential partners perceive them as more competent than other firms and as better able to offer more knowledge and relevant information (Ahuja 2000). In turn, the number of connections that the firm already possesses—its embeddedness—favors new collaborations. In network studies the popularity of actors (or centrality as defined by their number of linkages) is highly contingent on their popularity in prior periods. This continually recurring phenomenon (often referred to as preferential attachment, Barabási and Albert 1999, p. 510), is attributable to two effects. First, highly connected actors have broader access than less connected actors to information about potential partners (Gilsing et al. 2008). The more connections an actor has, the more information that actor automatically also has about the partners of his or her partners, and the more visible potential partners are. Second, potential partners perceive the central firm or actor as more attractive than other candidates because the information about the central actor diffuses more widely and quickly among a high number of potential partners than is the case for noncentral firms. Moreover, a high number of connections signals to potential partners a high level of competence and experience in managing and organizing alliances, a large repertoire of technical capabilities, and access to a broad and diverse knowledge pool (Ahuja 2000, Gulati 1999). Giuliani (2007), for instance, found that the most central actors in the knowledge network possess the most comprehensive knowledge base. The causal direction of this link is not clear, however.

Firms or actors do not have infinite capacity to establish new links. The returns on the creation of new links decrease with the total number of linkages because the costs of managing all the linkages increase as the information benefits decrease (Ahuja 2000, Hagedoorn and Frankort 2008). Besides, overembeddedness poses the risk of becoming locked in, of forfeiting access to novel and nonredundant information, and of thereby losing innovative potential (Gilsing et al. 2008, Uzzi 1997). Corroborating this curvilinear relationship for the composition of linkages as well, Wuyts et al. (2005) found that the diversity of the collaboration portfolio positively influences innovativeness up to a certain

optimal threshold. Actors whose popularity and opportunities are growing have to be increasingly selective in their partner choice (Ahuja 2000).
In the context of mutual agreements on collaboration and the search for the optimal linkages out of a pool of potential partners, reciprocity becomes paramount. Firms or actors want a return on the effort and resources they invest in the collaboration. Reciprocity creates trust among the potential partners and makes collaboration more likely and sustainable (Cantner et al. 2011). Furthermore, the balance between partners' invested effort and reciprocated learning determines how well the alliance functions and how long it endures. Unilateral learning or an imbalance of resources might result in asymmetric bargaining power and dependency (Hamel 1991, Khanna et al. 1998). Firms (actors) find that their attractiveness in terms of resources and efforts is reciprocated in collaborations with others similarly endowed. In sociological studies on the relations of individuals, the attractiveness of similarity has been termed homophily (McPherson et al. 2001, p. 370, Rogers and Bhowmik 1970, p. 526). In the context of R&D collaborations, homophily might be driven by the search for reciprocity. If so, then actors similar in experience and competence will exhibit higher reciprocal potential than dissimilar actors and will thus have mutual incentive to associate with each other (Cantner and Meder 2007).

3.2.2 The Dynamics of Tie Formation

Although much work has been done to identify factors that lead to the formation of innovative alliances, little is known about the factors that determine the continuation of these alliances (Dahlander and McFarland 2013). Because comprehensive longitudinal data on collaboration is difficult to find, most studies on innovation networks have relied on static analyses. Conceptual frameworks, too, such as Boschma's proximity approach, are basically static in nature (Balland et al. 2015). In addition, the relation between, the competence, proximity, and collaboration of a firm is characterized by strong interconnectedness. The embeddedness of firms also feeds back into the proximity to other actors, influencing their attractiveness as potential partners and future collaboration opportunities (Balland et al. 2015). The proximity of the partners changes throughout their bilateral collaboration as well, a shift that has consequences for its continuation. Both the underexplored coevolution of these factors and the evidence of the paradoxical effects of proximity and embeddedness make it unclear whether collaboration alliances are finite (develop toward a specific date of expiration) and whether one can use an alliance's continuation or termination to indicate an R&D alliance's success. These coevolutionary processes can be captured only by dynamic approaches.

Advances in this direction have been recently made mainly in the research on networks by scholars such as Balland et al. (2013), Broekel (2015), and Ter Wal (2014). They have developed frameworks for empirically analyzing the parallel development of proximity, structural embeddedness, and the overall linkage distribution. One of this literature's foremost contributions has been the inclusion of endogenous network forces (the feedback effects of structural position in the network) as an explanation for the probability of link formation other than relational effects (proximity) (Gilsing et al. 2008). Initial findings consistently have shown that the relevance of different proximity dimensions for the network configuration changes over time. Ter Wal (2014) elaborated the role of geographic proximity and triadic closure (which is close to social proximity; see Boschma and Frenken (2010)) in the network dynamics of the German biotech industry. He found that the effect of geographic proximity disappears over time, whereas the effect of social aspects increases in importance over time. Conversely, analysis of a creative industry, such as that for video games, showed that the effects of geographical and social proximity were pronounced throughout all stages of the industry, whereas cognitive aspects were relevant only in later stages (Balland et al. 2013). The interrelations between the various proximity dimensions have also come under study. Cognitive, social, institutional, and geographical proximity were found to co-evolve over time, whereas the association between cognitive and institutional proximity did not decrease over time (Broekel 2015). At the regional level, Cantner and Graf (2006) examined the network of innovators in Jena over two periods and found that the configuration of technological proximity among the actors changed over time in conjunction with the instability of collaboration. From this observation they concluded that the very process of knowledge exchange depletes the cooperation potential between two partners and eventually renders cooperation obsolete.

However, neither the various mechanisms that cause a change of proximities nor the association with actions at the microlevel has been sufficiently considered yet (Balland et al. 2013). Given this gap in the literature, we adopt a dynamic perspective to take a step toward describing the coevolution of collaboration decisions, proximity, and competencies. By analyzing the endurance of innovative ties and relating them to the change in the underlying cognitive and social proximity and to the competencies of actors, we go beyond the mere explanation of the formation of these linkages.

Two opposite dynamics have been identified in the ongoing debate about the effects that social aspects and cognitive aspects have on the continuation and discontinuation of collaborative ties, respectively. First, familiarity breeds trust and facilitates communication among partners (Gulati 1995), so building up link-specific social capital and the social proximity it entails contributes to the continuation and stability of linkages (Cantner et al. 2010, Gulati 1995, Gulati and Gargiuolo 1999). Second, an increase in cognitive proximity between collaborating partners promotes their mutual understanding but depletes the potential for novelty and reduces incentive to continue the collaboration (Wuyts et al. 2005). As for the development of innovation potential over time, we expect the positive returns of increased social proximity and mutual understanding between partners to be outweighed by the negative returns of excessively similar knowledge bases. The argument against long-term relations derives from the need for a diversity of knowledge for successful innovation (Nooteboom 1998, Gilsing et al. 2008). In summary, repeated ties accelerate the diffusion of information, whereas infrequent ties serve as a source of novel and nonredundant knowledge (Granovetter 2005).

Cognitive proximity

Adding to what has already been done, we unravel the multifaceted concept of cognitive proximity into overlap, reciprocal potential, and knowledge transfer and track their dynamics within the evolution of collaboration. Basically, the decision on forming or maintaining a link is continuously evaluated according to the potential gains in knowledge and in innovation (Hamel 1991, Wuyts et al. 2005). The knowledge endowment of partners can be considered a pool of potential knowledge flows. For these flows to be take place, two conditions must be met. First, a certain minimum similarity of knowledge bases, the overlap, is necessary to provide a basis for mutual understanding. The ability to absorb external knowledge is largely a function of the relatedness of the

knowledge bases of collaboration partners (Boschma 2005, Cantner and Meder 2007, Cohen and Levinthal 1990). Second, the exchange of knowledge requires potential knowledge that can be acquired because it is novel for the partner and not similar to the knowledge that the partner already possesses. The implication is that the dissimilarity of knowledge bases is also fruitful for potential knowledge flows. Collaboration will be established or continued only if the expected knowledge gains are positive.
From a dynamic perspective partners move along this proposed scale of cognitive proximity by increasing their overlap when collaborations evolve. After collaboration has been initiated, partners who are able to learn will experience an assimilation of knowledge bases that results in both an increase in overlap and a decrease in novelty potential (Balland et al. 2015, Nooteboom 1998, Wuyts et al. 2005). The positive effects that overlap has on mutual understanding will eventually be offset by the negative effects on novelty creation (Balland, et al. 2015). These dynamic reverse effects have been found in empirical studies on the persistence of collaboration between researchers (Dahlander and McFarland 2013) and on the performance of continuing cooperation between organizations (Beaudry and Schiffauerova 2011, Wuyts et al. 2005). At Stanford University, too much intellectual similarity (overlap) of the literature cited in publications by collaborating researchers has hampered the perpetuation of their collaborative ties (Dahlander and McFarland 2013). Lack of diversity decreases innovative performance in repeated collaborations as patent rates and the quality of patents diminish in long-term collaborations (Beaudry and Schiffauerova 2011), and the less variation a collaboration portfolio has, the less likely it is to result in technical novelty (Wuyts et al. 2005). We therefore assume that strategic actors who seek to maximize the benefits of collaboration for innovation will terminate their teamwork after it has exceeded the optimal level of overlap.

Hypothesis 3-1a:
The relation between the cognitive overlap of two actors and the likelihood of their continued collaboration follows an inverse-U curve.

Considering only the sheer overlap of knowledge, does not necessarily imply the full exploitation of learning potential, for the remaining novel and complementary knowledge in the partner's knowledge base is not taken into account (Mowery et al. 1998). The need to broaden that perspective becomes especially relevant in a dynamic examination of collaborations. If the knowledge bases of partners increase disproportionally to the overlap, the novelty potential does not necessarily decrease with overlap over time. Remaining potential for novelty is a key incentive to continue collaboration. Furthermore, collaborations as mutual agreements are established or continued only if both partners have incentives to engage in them. In general these incentives encompass a certain level of reciprocity: Actors want their invested efforts and competencies to be reciprocated. Seeking potential knowledge flows, actors search for collaboration that they can expect to reciprocate the amount of new knowledge they "offer" the partner (Cantner et al. 2011). The greater this reciprocal potential is, the more attractive they rate the collaborative opportunity to be (Cantner and Meder 2007). In other words, the likelihood of collaboration increases as the knowledge gains of the respective partners approach equality (referred to as the increase in reciprocal potential). We assume that the search for reciprocity in knowledge gains is also relevant for the continuation of collaboration.

Hypothesis 3-1b:
The reciprocal potential between two actors is positively correlated with the likelihood of their continued collaboration.

Apart from overlap and reciprocal potential, the very process of learning by the partners has consequences for the continuation or termination of collaboration (Hamel 1991, Khanna et al. 1998). We define learning as the outcome of successful knowledge transfer, that is, as the successful integration of external knowledge into the given partner's own knowledge stock. This definition includes the possibility that the newly integrated knowledge is applicable outside the cooperative activity as well (Khanna et al. 1998). When learning potential is exploited and knowledge has been transferred, the collaboration becomes obsolete to the partner who benefits from learning (Hamel 1991). Learning also influences the power distribution among the partners. An asymmetry in learning might lead to an imbalance in bargaining power and dependency structures. Competitive collaboration can be understood as a learning race in which the "first learner" gains a higher bargaining power than the lagging partner, who thereby becomes less attractive (Hamel 1991, Khanna et al. 1998). Hence, learning might cause the termination of collaboration by shifting the power balance and by decreasing innovative potential. In this regard the continuity of an alliance can be interpreted as learning failure rather than as success (Hamel 1991). We hypothesize that the degree of learning determines the continuation of collaboration. In line with the cognitive and power-related arguments, our assumption is that effective knowledge exchange will decrease the incentives to maintain the collaboration. If, on the contrary, knowledge is only shared but not transferred, actors will retain sufficient diversity in knowledge to benefit from the continuation of the collaboration. We thus expect that knowledge exchange between partners will lead to the termination of their collaboration, whereas mere knowledge-sharing will result in continued collaboration.

Hypothesis 3-1c:
Knowledge transfer between two actors is negatively correlated with the likelihood of their continued collaboration.

Social proximity

In the case of the collaboration among researchers at Stanford University, a shared history likewise has increased the probability of continuing the relationship (Dahlander and McFarland 2013). Established link-specific social capital seems to reinforce collaboration (Gulati 1995). A reason for this conjecture lies in the effect that social proximity has on the degree of comfort that accompanies communication. Social proximity is associated with trust, the establishment of mutually agreed social norms, and the control over undesired, noncooperative behavior such as opportunism (Boschma 2005, Granovetter 2005, Walker et al. 2003). Because social proximity is rooted in experience gained through successful cooperation, its supportive effects on knowledge exchange become increasingly evident with repetition of the cooperation. In this sense, increasing trust could explain the persistence of cooperation observed for alliances of firms (e.g., Gulati 1995, Mowery et al. 1998). However, the relevance of social aspects might be contingent on the context of the collaboration. Cantner et al. (2010), for instance, found that social capital as measured by the frequency of the contact plays a role only for innovative outcomes of cooperation with research institutes. In a dynamic context, we expect that social proximity as indicated by the experience that partners have shared through cooperation on innovation will promote future collaboration, all other factors remaining the same.

Hypothesis 3-2:
The likelihood of continued collaboration between two actors increases with their prior common experience.

Competence

Other factors that co-evolve with collaboration and that are subject to temporal changes are the actor's capabilities, overall experiences, and embeddedness in the overall network. Innovative capabilities and experience in managing collaborative agreements have been found to increase an actor's attractiveness as a collaboration partner (Ahuja 2000, Gulati 1999, Stuart 2000). As the number of innovative collaborations increases, the experience in running an alliance, managing skills, and developing innovative capabilities mounts, attracting further potential partners. Assuming that the condition of reciprocity needs to be fulfilled if collaboration is to be maintained, we expect the likelihood of continued cooperation to be positively associated with the combined innovative and collaborative experience of both partners.

Hypothesis 3-3a:
The greater the general inventive or innovative experience of both partners is, the higher the likelihood of their continued collaboration.

Hypothesis 3-3b:
The greater the general collaboration experience of both partners is, the more likely it is that their collaboration will continue.

The embeddedness of an actor as defined by the number of collaborative ties that the actor has established also determines the number of opportunities for additional collaborations. The mechanism by which the rich eventually get richer explains a certain path dependency in the evolution of networks: Central actors tend to become more central over time (Barabási and Albert 1999). This phenomenon is known as preferential attachment, or cumulative advantage

(Barabási and Albert 1999, Dahlander and McFarland 2013). This process might be explained by the broad access that central actors have to information about potential partners and by the high visibility that central actors have for other potential partners (Ahuja 2000). However, the reciprocity criterion applies as well. When seeking to maximize the benefits of the collaboration, central actors are more likely to find that their invested efforts are reciprocated by actors who exhibit the same degree of popularity. Moreover, the bargaining power of central firms is greater than that of the less connected actor. (Gilsing et al. 2008). If collaboration is to continue, then that power needs to be equally distributed among the partners so as to avoid unilateral dependence (Hamel 1991). Partners are therefore more likely to connect with each other and to maintain this connection if they possess a similar number of collaborative ties (Dahlander and McFarland 2013).

Hypothesis 3-3c:
The more similar the popularity of two actors is, the more likely it is that their collaboration will continue.

3.3 Methodology

In our theoretical considerations we identified three main factors that might explain the repetition of innovative linkages in our longitudinal study: (a) cognitive proximity between the cooperation partners, (b) social proximity between the cooperation partners, and (c) similarity in competencies that the partners bring to the collaboration. This section presents the database we used, the variables we created, and the methodology we applied.

3.3.1 Data

To construct potential and realized linkages, we used relational information found in patent applications. Successful collaboration leaves a trail in public patent data because patented inventions can be considered the output of a preceding intensive cooperative research process (Singh 2005). By definition, cooperative patents comprise inventive success in this context. Although patent data come with certain limitations (see Griliches 1990, Ter Wal and Boschma

2009), they offer a rich and comprehensive database on inventive activities. While working with patents, one must carefully define the scope of analysis in order to avoid the bias stemming from unobserved heterogeneity in patenting behavior (across industries and nations, for example). To reduce this bias arising from intercountry and interindustry differences, we narrowed our analysis to patents that were filed by German applicants in the field of biotechnology between 1978 and 2010. The biotech industry is characterized by a high propensity to patent and a high frequency of joint research (Griliches 1990, Powell and Grodal 2006, Ter Wal 2014). We gathered the data from the OECD REGPAT database (January 2012 ed.), which covers patent applications to the European Patent Office (EPO) and the United States Patent and Trademark Office (USPTO). To match the collaborative actors to their respective other patents, we used the OECD Harmonised Applicants' Names (HAN) database, "which provides a dictionary of applicants' names which have been elaborated with business register data, so that it can easily be matched by all users" (retrieved July 15, 2015, from http://www.oecd.org/sti/inno/oecdpatentdatabases .htm).

The use of patent data in our analysis requires some qualifications. First, our pool of potential collaborators encompassed all applicants that applied at least once for a patent between 1978 and 2010. The influx of entries meant that this pool was not fixed over time; it grew from year to year, so we had to deal with an unbalanced panel. Second, a link between actors occurred when actors appeared together as applicants on one patent document (co-application). The probability of false positives in detecting collaborations was assumed to be very small because a co-application reduces the applicants' claim to the patent. Third, it was debatable whether continuous cooperation was evident in patent data. If two applicants were persistently co-patenting, we assumed that they were still conducting joint research. In this sense, we were able to identify long-lasting relationships but may have underestimated the number of ongoing partnerships that did not result in patents. Fourth, patents have been established as a measure of technological capabilities (Mowery et al. 1996). The suitability of patent data as a proxy for firms' knowledge stock derives from the disaggregate information they convey. The International Patent Classification (IPC) offers a standardized and detailed technological classification system that enables one to assign the protected invention to a certain field of technology and to characterize the firms' research activities by constructing firm-specific technology portfolios (Griliches 1990, Jaffe 1986, Benner and Waldfogel 2008). Jaffe (1986) was one of the first researchers to use patent data as a proxy for technological competencies of firms. He constructed the knowledge portfolios as a vector of patent classes in which firms patented, and he computed the distances between technology vectors of firms to obtain a measure of proximity among them. Researchers subsequently adopted Jaffe's approach in using patent classes to show a firm's technology portfolio, technological distances among firms, or potential pools of knowledge spillover in the firm's environment (Benner and Waldfogel 2008, Boschma and Frenken 2010, Cantner and Graf 2006, Cantner and Meder 2007). We too, made use of this rich information by constructing the knowledge portfolios of the actors and tracing their changes over time. Because it is unfeasible to approximate knowledge portfolios of the individual inventor by means of patent information we focused our analysis on the organizational level.

3.3.2 Sample

The basic characteristics of the sample are presented in Table 3-1. The sample consisted of 197 firms that applied for patents with partners during the period under study—1983 to 2010. To analyze the dynamics of cooperation choice, we considered only the 91 firms that cooperated at least twice in this focal period and observed their collaborative behavior over the years that followed the firms' first appearance in the dataset. When a firm was cooperating in one year, we assigned it to each of the potential cooperation partners that were active in the pool at the same time. The pool of a firm's potential cooperation partners consisted of all patenting actors that were active in the focal year or had entered the sample before that point (Cantner and Meder 2007). For all possible combinations we assigned a 1 for each realized cooperation and a zero otherwise. Double pairs were excluded. The size of the pool of potential partners was nondecreasing from year to year. It amounted to a maximum of 2,369 potential partners.

Table 3-1 Description of Firms in the Sample Analyzed for the Dynamics of Cooperation, 1983–2010

Actors	
Characteristics	No.
Size of the pool of potential partners	2,369
Cooperating firms	197
One-shot	106
Repeaters	91
Hop-on-Hop-off	27
Mix-type	40
Persistent	24
Partner Diversity (Collaboration partners of focal firms)	
Min	1
Max	17
Median	2
Links	
Possible links	321,683
Realized links	293
Repeated links	60
Non-recurring link	138
Continuity of links (distribution of linkages across times of repetition, without duplicates)	
0	138
1	41
2	11
3	3
4	3
5	1
6	1

By definition, the collaborations we looked at included the subject firm and one potential partner in the pool that could be of any type (e.g., firm, university), implying that the observations were not symmetric. All told, the 27-year span covered by our analysis encompassed 321,683 possibilities to form dyads, of which 293 were ultimately realized.

When we grouped actors according to their overall collaboration activity over the whole period or over their all-time partner portfolio (Wuyts et al. 2005), we identified 106 firms that had collaborated only once (one shot), 27 that had collaborated at least twice but with different partners (hop-on, hop-off), 24 that had collaborated persistently with the same partner (persistent), and 40 that had pursued a mixed strategy (mixed type). For the purpose of our analysis, we focused on the firms that collaborated at least twice (i.e., excluding the one-shot collaborators). As for the continuity of linkages, we found that 60 of the 293 linkages were persistent and that 138 did not recur. Most of the 293 linkages had been repeated once, and the maximum number of times that a link was subsequently observed to have recurred was 6.

3.3.3 Variables

We aim to explain the reappearance of linkages that were established between 1983 and 2010. Assume, for example, that we observed a certain firm to have cooperated with a partner in 1997 and that this link recurred in 1998. This activity is what we call repeated cooperation. Assume also that recurrence of this link ceased from 1999 on. With our analysis we seek to explain why the variable for cooperation (the dependent variable) became zero after 1998. To do so, we constructed variables based on the cooperation partners' characteristics that had accumulated in the years before the cooperative relationship in 1998. All explanatory variables have been lagged by one year. Assuming that collaboration was the outcome of a mutual agreement, we derived the explanatory variables (except for Knowledge Transfer – *TransKnowledge*) by matching the attributes of a given firm with those of the partner it selected or was assigned to. In our analysis we have evaluated the mutual attractiveness of the collaboration opportunity according to social, technological, and experiential aspects of reciprocity. Table 3-2 gives a comprehensive description of the variables used.

Table 3-2 Variables used for explaining the reappearance of linkages between partners in the sample, 1978–2010

Use	Name	Description	Number of obs.	Mean	*SD*	Min	Max
Dependent variable	*Coop*	Binary variable indicating whether the pair actors cooperated in a certain year.	321,683	0.0009	0.0302	0	1
H3-1a	*RlOverlap*	Continuous variable indicating the overlap of the partners' knowledge relative to the overall knowledge both partners possess. Measured as the ratio of common IPC classes to the sum of all IPC classes both partners cover.	319,323	0.05197	0.0662	0	0.5
	RlOverlap^2	The squared values of knowledge overlap.	319,323	0.0071	0.0158	0	0.25
H3-1b	*RciPot*	Continuous variable ranging from zero to one and measuring the ratio between the minimum and maximum of nonoverlapping knowledge classes of both partners. The higher the value, the closer the partners are to having an equal number of potential new classes.	319,256	0.2307	0.2730	0	1
H3-1c	*TransKnowledge*	Binary variable indicating whether a knowledge exchange occurred in the previous period.	321,683	0.0006	0.0254	0	1

Table 3-2 continued

Use	Name of Variable	Description	Number of obs.[a]	Mean	*SD*	Min	Max
H3-2	*CoopExp*	Count variable to measure social proximity. It indicates how often the partners cooperated before the cooperation in question.	321,683	0.0016	0.0655	0	7
H3-3a	*DyadSinglePAT5*	Logarithm of the sum of single patents held by each of the partners in the previous 5 years.	311,728	4.4010	2.7340	0	10.75658
H3-3b	*DyadCoopPAT5*	Logarithm of the sum of the number of co-patents held by each partner in previous 5 years.	311,728	3.4156	1.6567	0	8.9363
H3-3c	*DCentrality*	Absolute difference in the degree centrality of the two partners.	321,683	1.4467	0.9919	0	11
Controls	*DPatAge*	Difference in age (year of first patenting activity) of the two partners.	321,683	7.7953	6.3583	0	30
	DStatus	Binary variable indicating whether the partners are of the same type: 1 means both are different, zero means both are firms.	321,683	0.5480	0.4977	0	1

Table 3-2 continued

Use	Name of Variable	Description	Number of obs.[a]	Mean	*SD*	Min	Max
Interactions	*TransKnowledge**[6] *CoopExp*	Interaction of knowledge *TransKnowledge* with *CoopExp.*	321,683	0.0010	0.0560	0	7
	*TransKnowledge** *RlOverlap*	Interaction of *TransKnowledge* with *RlOverlap.*	319,323	0.0001	0.0035	0	0.3478

[6] The * represents that the two variables are multiplied.

3.3.3.1 Dependent variable

The dependent variable, *Coop,* represents the cooperation between two actors in the current year and is binary. It has the value of 1 if there is cooperation between the actors as a pair; zero, if there is no cooperation. With our interest in explaining continuous collaboration and the dissolution of cooperation, previously existing nonrecurring links (expressed technically by the change of the dependent variable from 1 to zero) are detected by the variable for common experience (see Social proximity between the cooperation partners below).

3.3.3.2 Independent variables

<u>Cognitive proximity between the cooperation partners</u>

Overlap

A widely accepted procedure to operationalize the construct of cognitive proximity is to categorize the innovative pursuits of the actors in some way. For this purpose, the IPC offers a practical, detailed system for documenting their technological activities. In empirical studies it is claimed that the IPC is useful for measuring technological proximity as an aspect of cognitive proximity (Gilsing et al. 2008, pp. 1719-1720, 1723). In keeping with previous studies (e.g. Jaffe 1986, Cantner and Graf 2006, Cantner and Meder 2007, Gilsing et al. 2008), we, too, adopted this resource to classify patent documents and used technological proximity as a proxy for the multifaceted concept of cognitive proximity.
To test hypothesis 3-1a, we included a simple measure used in previous studies (e.g., Singh 2005, Cantner and Graf 2006). To observe whether a minimum level of mutual understanding of both partners was guaranteed, we calculated the two partners' overlapping areas of knowledge (technically, just the count of the IPC classes that partners or potential partners share). To correct for the fact that a potential overlap is more likely between firms with relatively large portfolios than between for firms with smaller ones, we divided the overlap by the sum of the IPC classes in the portfolios of both partners, using the relative overlap as one measure of cognitive proximity (*RlOverlap*). We also included this measure as a quadratic term to capture the trade-off between minimum levels of knowledge overlap (as a warrant for mutual understanding) and max-

imum levels of overlap (as a hurdle that knowledge redundancy poses to innovation) (*RlOverlap2*).

Reciprocal potential

Following Cantner and Meder (2007), we tested hypothesis 3-1b by operationalizing the potential knowledge benefits from a potential collaboration as the relation between partner A's and partner B's new knowledge that is brought to the collaboration. However, we extended the approach of that earlier study by differentiating the individual classes that were new to the partner rather than solely considering the absolute number of patents. We counted the number of nonoverlapping IPC classes for each actor and took the ratio between the minimum number and the maximum number of new knowledge classes. This measure is named *RciPot.* It is a continuous variable that ranges between 0 and 1, taking a 1 when the amount of new knowledge that the one partner offers is equal to that of the other (perfect reciprocity). The greater the divergence between the amount of partner A's and partner B's nonoverlapping knowledge (i.e., the less reciprocal the gain is between the partners), the more the measure of potential benefit approaches zero.

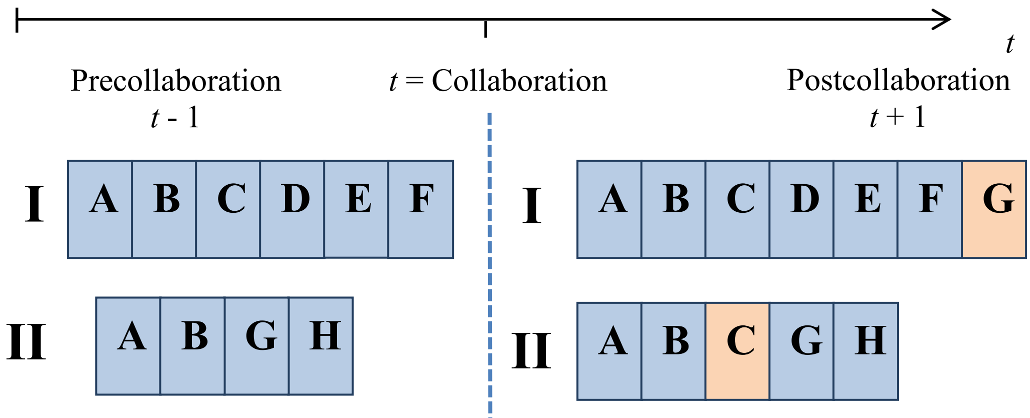
Knowledge transfer

To test hypothesis 3-1c, we needed to measure the knowledge transfer between collaborators. Citations of previous documents (patents and publications) pertaining to the patent have become a favored instrument with which scientific authors detect knowledge spillovers (e.g., Griliches 1990, Hall et al. 2001, Jaffe et al. 1993, Mowery et al. 1996, Nelson 2009, Nomaler and Verspagen 2008, Schmoch 1993, Singh 2005). A frequent criticism, however, has been that patent citations may not imply real knowledge flows, for many citations are added by the patent examiner rather than the inventor or applicant.

We took a different avenue and measured knowledge transfer between partners. To do so, we defined the vector of a firm's patented technological classes as its cumulated knowledge stock and compared pre- and post-collaboration knowledge stocks. We defined knowledge transfer as the appearance of a new patent class in the firm's patent portfolio after the collaboration had taken place (i.e., after the co-patent had been filed). To attribute the portfolio changes to the cooperation, the newly added class had to have been part of the partner's pre-collaboration knowledge base. This measure enabled us to differentiate pure knowledge-sharing (as the pure access to knowledge) from knowledge exchange (the integration of new knowledge into the firm's own knowledge base). We assumed that if a class was subsequently assigned to single patents, then the knowledge had been successfully integrated and was applicable afterward without further collaboration. Used in conjunction with this procedure, the binary variable *TransKnowledge* indicates whether knowledge has been exchanged in prior collaborations. This variable takes the value 1 if either partner has gained new knowledge; otherwise it takes the value zero. That is, the variable captures both symmetric and asymmetric learning.

Our three measures of cognitive proximity—*RlOverlap, RciPot*, and *TransKnowledge* - do not develop independently of each other. Their changes over time go hand in hand. Figure 3-1 illustrates the dynamics of these three variables. Two actors, I and II, hold specific knowledge portfolios before cooperating with each other (pre-collaboration). Actor I's portfolio comprises ABCDEF; actor II's, ABGH. The knowledge overlap in t1 is given by AB and amounts to .2, relative to the overall knowledge. The reciprocal potential equals .5 because actor II possesses two knowledge units that actor I can gain as opposed to four knowledge units that actor II might be able to acquire from actor I. In other words, actor I can gain at most only half the amount of knowledge that actor II, the partner, stands to gain. Formulated differently, actor II can earn twice the amount of new knowledge that is being offered to actor I. In this example, the potential gains are unequal. Assume that collaboration then leads to symmetric learning in that C and G are exchanged. Actor I's post-collaboration portfolio is thereby enlarged to ABCDEFG; actor II's, to ABCGH. As a result, the overlap has increased to ABCEG and amounts now to .3 in relation to the overall knowledge possessed by the two firms. In turn, the ratio between the potential knowledge gains has decreased to .3 because actor II now offers only one new knowledge unit to actor I, whereas actor I now offers three knowledge units to actor II. The potential for knowledge flows has thus decreased and become more uneven. The attractiveness of this fictive alliance and the likelihood that it will continue have therefore declined. This example illustrates the case of knowledge having been efficiently exchanged. When actors collaborate but are unable to integrate new knowledge into their stock, then knowledge has only been shared and the collaboration is more likely to continue. In this sense, a continuation of collaboration can be interpreted as a failure to learn (Hamel 1991).

Figure 3-1 The dynamics in cognitive proximity and collaboration (example).



Overlap $_{t-1}$

$$\frac{AB}{ABCDEF + ABGH} = \frac{2}{10} = 0.2$$

Reciprocal Potential $_{t-1}$

$$\frac{GH}{CDEF} = \frac{2}{4} = 0.5$$

Knowledge Transfer $_{t-1}$

Overlap $_{t+1}$

$$\frac{ABCG}{ABCDEFG + ABCGH} = \frac{4}{12} = 0.3$$

Reciprocal Potential $_{t+1}$

$$\frac{H}{DEF} = \frac{1}{3} = 0.3$$

Knowledge Transfer $_{t+1}$

$I. \rightarrow II.: C$

$II. \rightarrow I.: G$

Social proximity between the cooperation partners

To test whether the probability for the creation or re-creation of a link increases with the social proximity between the partners (hypothesis 3-2), we included a variable for common experience, *CoopExp*, as a proxy for social proximity. CoopExp measures how often the pair was cooperating prior to the cooperation in question. The number of prior research projects with the partner is commonly used as a measure of the strength of the tie and is assumed to capture the trust and ease of communication between the partners (Cantner and Meder 2007).

Similarity in competencies

Innovative capabilities

Patents are an approved proxy for innovative activities, for the number of patents an actor holds is highly correlated with his R&D activities (Mowery et al. 1996). To elaborate on the relation between accumulated technological capital and the continuation of linkages (hypothesis 3-3a), we therefore added up the single patents (not co-patents) that both partners owned in the five years prior to their collaboration and regarded that sum as a proxy for their accumulated innovative capabilities (*DyadSinglePAT5*). To delimit the domain of the variable, we took the logarithm of these values. We limited the observation period to the five years preceding the collaboration of the two firms, assuming the knowledge to be almost obsolete thereafter and accounting for the depreciation of innovative capabilities. Studies on the depreciations of R&D activities (Czarnitzki et al. 2006, Hall 2007, Edworthy and Wallis 2009) have proposed that R&D investment is completely depreciated after 3 to 5 years.

General collaboration experience

Analogously, to capture the attractiveness of the collaboration opportunity in terms of management ease, we take the sum of the shared patents (co-patents) that both actors held in the five years prior to the collaboration as a proxy for their accumulated collaboration experience (*DyadCoopPAT5*). Since we want to detect the general collaboration experience, this measure adds up all collaborations except the collaboration in question. The greater the collaborative experience is the higher is the likelihood for further collaborations (hypothesis 3-

3b). Here we also assume average capability depreciation after five years and apply the logarithmic transformation to delimit the range of the variable.

Popularity

Giuliani (2007) argues, due to reciprocal incentives, it is more likely that popular (as measured by their number of other linkages), central actors connect to similarly embedded actors. We believe that the potential for knowledge spillovers might be greater when partners are equally popular and possess a similar pool of potential knowledge sources (links). To test this relation (hypothesis 3-3c) and following Dahlander and McFarland (2013), we used the absolute difference between the two partners' degree of centrality (the number of links) in the year before their (potential) collaboration. We called this variable *DCentrality*. Theoretically, this measure is closely related to the general collaboration experience. In our analysis, however, it captures the reciprocity of popularity in collaboration activity rather than the pure amount of previous collaboration activity.

3.3.3.3 Control variables

Apart from technological, social, and competence aspects, we also wanted to control for additional effects stemming from organizational and age similarity. Both variables might increase the likelihood of collaboration due to ease of communication when the cooperating partners are exposed to the same institutional factors and environments (organizational similarity) or when they have had the same amount of time to operate in these environments and to accumulate experience and resources (age similarity). Organizational dissimilarity—*DStatus*—is a binary variable taking the value 1 when the two actors differ in organizational nature and zero when they are of the same organizational type (interfirm collaboration). *DPatAge* is the absolute difference between the ages of the actors (measured as the length of appearance since their first appearance on a patent). Our age variable is also assumed to capture the effect of firm size because the age and the size of the firm are usually highly correlated.

3.3.4 Estimation Strategy

The choice of a pair of partners to cooperate was modeled as the probability of observing the realization of a link ($coop_{i,j,t}$ taking the value 1) contingent on the explanatory variables we have discussed in this section. The decision to collaborate in the form of a co-patent is a binary one (see Figure 3-2). We therefore estimate the following logistic model (see Kennedy 2009).

Figure 3-2 Formal representation of the logistic model to explain the binary cooperation decision

$$
\begin{aligned}
&\log\left[\frac{P(Coop_{i,j,t}=1)}{1-P(Coop_{i,j,t}=1)}\right] \\
&= \beta_0 \\
&+ \beta_1 RlOverlap_{i,j,t-1} + \beta_2 RlOverlap\char`^2_{i,j,t-1} + \beta_3 RciPot_{i,j,t-1} + \beta_4 TransKnowledge_{i,j,t-n} \\
&+ \beta_5 CoopExp_{i,j,t-n} \\
&+ \beta_6 DyadSinglePAT5_{i,j,t-1} + \beta_7 DyadCoopPAT5_{i,j,t-1} + \beta_8 DCentrality_{i,j,t-1} \\
&+ \beta_9 TransKnowledge_{i,j,t-n} * CoopExp_{i,j,t-n} \\
&+ \beta_{10} TransKnowledge_{i,j,t-n} * RlOverlap_{i,j,t-1} \\
&+ \beta_{11} DPatAge_{i,j,t} + \beta_{12} DStatus_{i,j,t} \\
&+ \varepsilon_{i,j,t}
\end{aligned}
$$

We included all realized and potential i,j combinations over the period from 1983 to 2010. To avoid potential biases from confining our sample to collaborative actors only, we included all possible combinations between the focal firms and all actors that had patented at least once. However, inclusion of combinations with all potential actors in the sample (even those that have never collaborated) introduces a source of bias due to unobserved heterogeneity. That is, control-group dyads that were never realized might differ systematically in unobserved factors from dyads that were realized at least once. These differences in unobserved characteristics might account for systematic differences in the general propensity of actors to collaborate. Furthermore, other specific factors that are not observable and therefore cannot be included in our model might have caused the formation of each dyad (Gulati and Gargiulo 1999, Heckman 1981). To account for pair-specific heterogeneity, we applied a random-effects panel model by including a random intercept for each pair. We thereby assumed that the unobserved differences in the dyads were the results of a random process. However, this method also comes with the strong assumption that the unobserved factors are not correlated with any of the explanatory variables. This assumption is hard to test empirically. Conversely, the fixed-effects estimator would remove these time-invariant factors but would dramatically shrink the size of the sample. This change would come at a cost: The number of observations would drop from more than 300,000 to 501. Moreover, random-effects estimation allows us to have the model include additional time-invariant variables, such as *DStatus*. Given these considerations, we prefer the random-effects over the fixed-effects model.

Another issue that arises in the analysis of network data is the dependence of observations. The observations are not completely independent; individual actors might be part of multiple dyads. Consequently, the estimates are consistent, but the standard errors might be underestimated (Kennedy 2009). Because we could not make any distributional assumption, we obtained robust standard errors by resorting to bootstrapping methods for panel data. We calculated the standard errors from the empirical distribution that was drawn by resampling the original dataset in 1,000 iterations. Another form of bootstrapping commonly used to analyze dyadic data is that of gathering the empirical distribution by repeated random permutation of the complete adjacency matrix—an approach known as multiple regression quadratic assignment procedures (MRQAP). Although this method has proven to be appropriate for linear models with continuous a dependent variable, it is still unclear how it performs when employed to analyze binary models (Broekel et al. 2014, Dekker et al. 2007). Besides, MRQAP has not been tested much in panel settings.

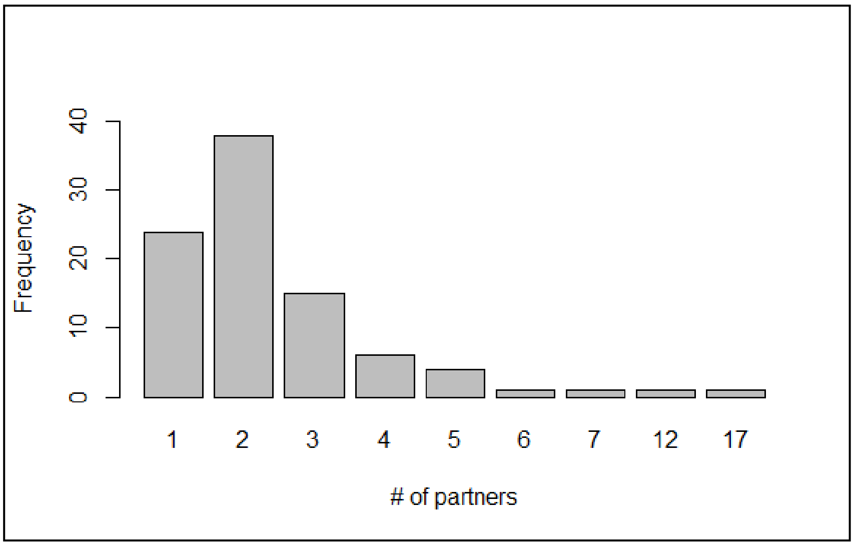
3.4 Results

3.4.1 Descriptives

3.4.1.1 Diversity in partner portfolio

For an initial overview of the diversity of the firms' partner portfolios, we considered the number of different partners firms cooperated with in the years from 1978 to 2010. Table 3-1 contains summary statistics about the number of partners and the continuity of links. As shown by the distribution of actors across the different partners (see Figure 3-3), most firms cooperated with two different partners, the median being 2. Only a few firms cooperated with a larger variety of actors. The maximum number of different partners in one portfolio was 17. In other words, one firm cooperated with 17 different actors during the period under study. For the firms in our sample, the implication was that repeated collaboration with only one partner was not a dominant behavior.

Figure 3-3 Diversity of the partner portfolio among firms in the sample



3.4.1.2 Dynamics of link formation

Concerning the recurrence of links, we found that 138 of the 293 realized links came about just once (non-recurring), whereas 60 links were repeated at least once (the sum of repetitive links was 155). Without double-counting the repeated links, we found 198 realized combinations, of which most (138, or 70%) were non-recurring. Most (41) of the sustainable links were repeated only once, and the maximum number of link repetitions was 6. Unlike the findings reported by Gulati (1995) as well as Gulati and Gargiulo (1999), who found stability in link formation, our first findings suggest that firms are inclined to change partners regularly rather than repeat collaboration with the same partner. Our findings complement the results by Wuyts et al. (2005) and Cantner and Graf (2006) in that the search for diversity of knowledge sources tends to lead firms to switch their R&D partners.

3.4.2 Estimation Results

Table 3-3 shows the bilateral correlations between the variables included in the estimations. With regard to correlations between the explanatory variables, we do not seem to have a severe problem of collinearity. With respect to the correlation between the explanatory variables and the dependent variable (*Coop*), we find that *RlOverlap, TransKnowledge, CoopExp, DyadSingle-PAT5, DyadCoopPAT5,* and *DStatus* are slightly positively correlated with cooperation, whereas *RciPot, DCentrality,* and *DPatAge* show a negative sign.

To gain a more detailed understanding of the forces that determine the partner choice, we ran a random-effects logistic regression on our panel data. Table 3-4 shows the outcome of our estimations for seven model variations. The results for the base model which comprises the two control variables, *DStatus* and *DPatAge*, are shown in the last column. We found that *DStatus* was highly significant and positively linked to the probability to cooperate (*Coop*), indicating that firms prefer to cooperate with partners that are of a different organizational form.

Concerning the dynamics of cognitive proximity, we analyzed three dimensions: overlap (*RlOverlap*), reciprocal potential (*RciPot*), and knowledge transfer (*TransKnowledge*). First, we found that the squared term of the relative overlap (*RlOverlapl2*) between the knowledge bases of the two partners was positively and highly significantly related to the probability of collaboration. However, we found no evidence of a moderate overlap and, hence, no support for hypothesis 3-1a. When controlling for combined effects of experience and overlap (see the column labeled "Interactions"), we found only a pure positive correlation between overlap and the likelihood of collaboration. Thus, the degree of mutual understanding seems to increase the likelihood that linkages will be recreated.

Second, our impression of the search for diversity as illustrated in Figure 3-2 was confirmed by the results of our estimation. We found that firms were more likely to reconnect with actors who differed from them in the amount of potentially new knowledge than with actors who were the same or similar in that respect. The negative relation between reciprocal potential (*RciPot*) and the likelihood of collaboration indicates that reciprocity in knowledge gains is not a necessary precondition for the continuity of collaborations. Our result was opposite to the assumed relation stated in hypothesis 3-1b.

Third, concerning hypothesis 3-1c, we did not find a significantly positive relation between collaboration and previous knowledge transfer (*TransKnowledge*). Our results seem to contradict our hypotheses on the relevance of knowledge diversity in the evolution of cooperation. Concerning cognitive proximity, the need for mutual understanding seems to predominante over need for reciprocity in potential knowledge gains.

Regarding social proximity, we found no empirical connection between the chances for cooperation and prior common experience (*CoopExp*), a result that does not support our suggestion in hypothesis 3-2 that the propensity of collaboration increases with prior common experience.

Even though common experience did not play a significant role in partner choice among the firms in our sample, the combined overall cooperation experience (*DyadCoopPAT5*) was positively and significantly associated with the re-creation of linkages. That is, choices to collaborate were preferred when at least one actor exhibited a large amount of accumulated capabilities in managing cooperation. This finding is consistent with the results reported by Gulati (1999), who observed the same supportive effect that an actor's general experience with collaboration has on that actor's chances of forming linkages.

Table 3-3 Correlation Table of the variables used for analyzing the dynamics of cooperation

	Variables	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*
1	*Coop*	1										
2	*RlOverlap*	0.0471*	1									
3	*RlOverlap*^{2}	0.0673*	0.9098*	1								
4	*RciPot*	-0.0079*	0.2081*	0.1861*	1							
5	*TransKnowledge*	0.2332*	0.0250*	0.0219*	-0.0019	1						
6	*CoopExp*	0.2479*	0.0265*	0.0253*	-0.0058*	0.6577*	1					
7	*DCentrality*	-0.0182*	-0.0381*	-0.0255*	0.0252*	0.0059*	-0.0004	1				
8	*DyadSinglePAT5*	0.0105*	-0.1366*	-0.1083*	-0.4396*	0.0241*	0.0172*	0.0222*	1			
9	*DyadCoopPAT5*	0.0215*	-0.1455*	-0.1079*	-0.3693*	0.0351*	0.0298*	0.0770*	0.6526*	1		
10	*DStatus*	0.0123*	-0.0120*	-0.0001	-0.0652*	0.0071*	0.0058*	0.0005	-0.1169*	-0.0053*	1	
11	*DPatAge*	-0.0021	-0.2131*	-0.1684*	-0.1866*	-0.0029	-0.0046*	0.0937*	0.1638*	0.2781*	-0.0054	1

*p<=.01

Table 3-4 Estimation results on repeated cooperation

Method	Random-Effects Logistic Regression							
Dep.Var	*coop*							
Population	All potential pairs per period							
	H 3-1a		H 3-1b		H 3-1c		H 3-2	
RlOverlap	5.5655							
	(1.58)							
RlOverlap^2	49.711	***						
	(5.59)							
RciPot			-2.2486	***				
			(-3.88)					
TransKnowledge					0.9032			
					(1.19)			
CoopExp							0.0077	
							(0.03)	
DStatus	1.247	***	1.1283	***	0.998	***	1.0228	**
	(4.18)		(4.39)		(4.40)		(4.29)	
DPatAge	0.0743	***	-0.0003		-0.0041		-0.0039	
	(-3.43)		(-0.01)		(-0.23)		(-0.23)	
Constant	-20.9707	***	-17.1154	***	-14.1513	***	-14.3361	**
	(-15.62)		(-13.09)		(-8.44)		(-8.17)	
No. of Observations	319,323		319,256		321,683		321,683	
No. of Groups	142,417		142,384		142,984		142,984	
LR chi2	-1,610.31		1,019.03		479.56		613.07	
Prob > chi2	0		0		0		0	
Wald chi2(3)			33.08		19.68		19.89	
Wald chi2(4)	164.27							
/lnsig2u	3.4286		3.2234		2.7003		2.7382	
sigma_u	5.5528		5.0114		3.8579		3.9318	
rho	0.9036		0.8842		0.819		0.8245	

Robust *z* statistics in parentheses.
*p<= .1 **p<= .05 *** p<= .01

Table 3-4 continued

Method	Random-Effects Logistic Regression					
Dep.Var	*Coop*					
Population	All potential pairs per period					
	H 3 a–c		Interactions		Controls	
RlOverlap			27.0777	***		
			(7.79)			
TransKnowledge			1.6796			
			(1.53)			
CoopExp			-0.1455			
			(-0.33)			
DyadSinglePAT5	-0.0431					
	(-1.00)					
DyadCoopPAT5	0.6109	***				
	(9.53)					
DCentrality	-1.1718	**				
	(1.97)					
*TransKnowledge**			-0.9984			
CoopExp			(-1.51)			
*TransKnowledge**			-4.3422			
DStatus	1.1042	***	1.4245	***	1.0215	***
	(4.42)		(4.06)		(4.15)	
DPatAge	-0.0393	**	0.1149	***	-0.0039	
	(-2.19)		(4.69)		(-0.23)	
Constant	-14.8631	***	-24.0424	***	-14.3457	***
	(-7.66)		(-8.81)		(-9.34)	
No. of Observations	311,728		319,323		321,683	
No. of Groups	139,318		142,417		142,984	
LR chi2	542.03		-1604.7		-1808.19	
Prob > chi2	0		0		0	
Wald chi2(5)	178.66					
Wald chi2(7)			146.14			
Wald chi2(2)					17.62	
/lnsig2u	2.7401		3.6029		2.7404	
sigma_u	3.9355		6.05834		3.9362	
rho	0.8248		0.9177		0.8249	

Robust *z* statistics in parentheses.

*p<= .1 **p<= .05 *** p<= .01

The importance of cumulative advantages is also reflected in the negative relation between collaboration propensity and the difference in popularity (*DCentrality*). While firms did not search for reciprocal knowledge benefits, they tend to be guided by reciprocal incentives when it comes to accumulated cooperation capabilities and experience. Our results indicate that firms prefer to link up with actors that offer an equal amount of accumulated resources. Dahlander and McFarland (2013) found the same negative association for the difference between the "cumulative advantage" of both partners (p. 72) and the persistence of collaboration between researchers at Stanford University. Conversely, the common cumulative innovative potential as measured by the total number of single patents held by both actors (*DyadSinglePAT5*) seems rather irrelevant when it comes to partner choice. Therefore, we find support for our hypotheses 3-3b and 3-3c but not for hypothesis 3-3a.

Our findings lend support to the hypothesis that similarity in knowledge and accumulated capabilities enhance the attractiveness of collaboration options and link maintenance. Nevertheless, firms also seek some degree of heterogeneity in the controls *DStatus* and *DPatAge*, for the probability of repeated collaboration increases when the partner is not a firm or when the partner is significantly different in patenting experience. However, these findings can be partially attributed to the specificities of research in biotechology. One reason is that relationships between industry and the university are prevalent in German biotechology. Because the innovation process is rather linear, with discoveries being introduced by public research institutes, collaboration between industry and the university is an important mechanism of technology transfer and thus increases its likelihood. Furthermore, the influence of the difference between the patenting ages of the partners might reflect another widespread form of collaborative combination in biotechology: the joint research by young, small companies as the creative engine and large pharmaceutical companies as a source of financial resources (McKelvey 1997, Powell et al. 1996, Ter Wal 2014).

In summary, our findings generally suggest that both similarity and diversity of actors afford incentives to form alliances. Similarity plays a specific role in partner choice with regard to general collaboration experience (*DyadCoopPAT5*) and the accumulation of resources (*DCentrality*). Actors seek to connect to actors who can reciprocate their general collaboration expertise and provide a certain basis for mutual understanding. The reciprocity in knowledge gains and the amount of innovative capability seem to play a comparatively subordinate role. As far as organizational similarity and patenting age are concerned, actors are inclined to choose diverse partners.

3.5 Conclusion and Further Research

The aim of this study was to elaborate on the coevolution of several attributes of cognitive proximity, social proximity, and similarity in competencies as collaboration between two actors progresses. We have contributed to the debate on whether networks are rather stable (i.e., with actors always cooperating with the same partners) or volatile (i.e., with actors changing partners regularly). Our findings suggest that firms are prone more to switching their cooperation partner than to repeating the collaboration with a given partner. We found no significant effect of knowledge transfer and prior common experience on repeated link formation. Instead, we found that firms prefer to cooperate with a partner whose knowledge bases and accumulated collaboration experience are rather similar to their own and whose organizational nature and patenting age rather dissimilar to their own. We did not find evidence to support the hypothesis that potential for innovation and collaboration decreases as the overlap of the knowledge bases increases (Nooteboom 1998, Wuyts et al. 2005, Gilsing et al. 2008).

Our methodology has limitations and drawbacks that one must consider when interpreting the final results. First, the revelation of realized linkages heavily depends on the patenting practices among actors (e.g., cross-patenting or cases in which a central institution may administrate the patenting process and is therefore the only applicant). Including only those collaborations that are defined by co-application might underestimate the number of actual linkages. Yet if we were also to take account of the connections realized through shared inventors, we might overestimate the number of linkages (Ter Wal and Boschma 2009). In addition, we expect the number of disregarded cases to be rather small because inventor mobility is rare in Europe (Ter Wal and Boschma 2009). Crescenzi et al. (2013) estimated that barely 5% of inventors change their employer. A closely related drawback to our methodology is the underrepresentation of informal ties, for we considered only formal collaboration agreements. Prior studies have emphasized the importance that informal ties have for innovative outcomes (e.g., Powell and Grodal 2006), but it has been found that formal ties, especially in the life sciences, are generally preceded by informal ties (Powell et al. 1996). On this basis we argue that preceding informal ties are manifest in formal ties and are therefore captured in the study of the latter.

Second, by focusing on the research of the dynamics in bilateral R&D collaboration, we set aside the study of the effects of the micromechanism on the overall network structure. We thereby also opted to forgo explicit consideration of the feedback effects that an actor's position in the overall network has on partner choices at the microlevel. We tried to control for this limitation by incorporating information on whether an actor was highly connected (central) or rather peripheral and by adapting the standard errors accordingly. However, recent research on networks has made advances regarding the explicit modeling of endogenous structural mechanisms such as triadic closure and preferential attachment (Broekel et al. 2014). Our analysis could be extended by elaborating the overall network evolution as a result of partner choice at the microlevel which is itself determined by similarity and diversity aspects. Stochastic actor-oriented models, for instance, allow for examination of the relationship between the individual partner choice and overall network dynamics (Balland et al. 2013). In this context, however, it is debatable to what extent firms can directly influence and are aware of the network beyond their ego network (direct connections) (Gilsing et al. 2008).

The third concern about studies that focus on analyzing a certain pattern in a specific industry is the generalizability of their results. Application of our results if limited, for example, by the appearance of patterns that might be caused by industry specificities. However, some of the factors that our analysis identifies (e.g., positive effects of overlap, the reciprocal cumulative advantage and reciprocal general collaboration experience) have also been observed in other environments and levels of observations (Cantner and Meder 2007, Dahlander and McFarland 2013, Gulati 1999).

In view of our results and the type of analysis suggested with this study we take a further step into disentangling the coevolution of the proximity of collaboration partners and the formation respectively repetition of cooperative ties. In doing so we already took on board factors that go beyond dyadic relationships such as network characteristics. Extending this dimension in future research will help to find a better understanding of the dynamics of cooperation networks being at the core of clusters as well as local and regional innovation systems.

4. On regional innovator networks as hubs for innovative ventures

4.1 Introduction

Innovation can be defined as "a process that begins with an idea, proceeds with the development of an invention, and results in the introduction of a new product, process or service to the marketplace" (Edwards and Gordon 1984, p.1). Both, (i) the founding of a new firm and (ii) the survival of existing firms are substantially affected by this complex construct. As to (i), innovation is considered to be one of three important characteristics entailed by entrepreneurship (OECD 1998). This view stems from Schumpeter's (1912) suggestion that innovation is a creative *modus operandi* of an entrepreneur (Nijkamp 2011). Audretsch and Lehmann (2005, p. 1192) formulate the relationship as follows: "…entrepreneurship is an endogenous response to the potential for commercializing knowledge that has not been adequately commercialized by the incumbent firms". Thus, entrepreneurs discover an opportunity to exploit a new technology (Shane 2000) and implement this by founding a firm. As to (ii) by creating new variations, new innovative firms compete with incumbent firms, which force the latter to improve or change their production processes or product portfolios. Under these conditions, incumbent firms must be innovative if they are to survive (Brown and Eisenhardt 1997). Non-innovators will fall behind, while first movers respectively firms with an entrepreneurial orientation secure a position of competitive advantage (Lumpkin and Dess 1996, Pyka 1999).

Before World War II, and thus also in Schumpeter's theory, the linear model of innovation was the generally accepted one (Kline and Rosenberg 1986). In this model, events flow smoothly in a one-way street. First, one does research, after that follows development which is followed by production which itself is followed by marketing. Looking more closely on how new ideas are created and innovations come up, according to the definition of Edwards and Gordon (1984), a more complex process as compared to the linear model is going on. Kline and Rosenberg (1986) tried to formalize this complex process and proposed the 'chain-linked model' which entails five different paths of activity and considers feedbacks between the different stages of innovation. This model however does not recover, where feedbacks and information flows are coming from. Over the last decades the concept of collective invention and innovation, brought up by Allen (1983) and von Hippel (1987), has been developed which answers this question. This concept has been said to form the basis for the systemic view of innovative activities and the innovation process (Cantner 2000). Innovations are considered as new combinations that are brought to the market (Schumpeter 1912). Consequently, they require recombining different pieces of existing knowledge (Cantner and Meder 2007). These pieces of knowledge, necessary to successfully innovate, may not be in the immediate reach of an actor or firm but may rather lay outside (Cowan et al. 2006). Thus, access to external knowledge may be an important prerequisite for innovative success. At this point, collectivity comes into play. No single individual or firm can solve all problems (Ejermo and Karlsson 2006) since it does not hold all knowledge available in the world. Especially invention processes are based on the combination of various pieces of knowledge which are possessed by various economic actors. With this perspective in mind, we can argue that invention and innovation activities rely on processes of collective or social learning and exchange of knowledge between actors (Lundvall 1992, Doloreux and Parto 2005), whereas learning is the process whereby existing knowledge is selected and combined based upon a new perspective (Ejermo and Karlsson 2006). Consequently the creation of innovation requires knowledge spillover-producing interaction. These knowledge spillovers can happen deliberately, for example in the context of research collaborations, or involuntary and unintended.

In this research paper, we use the approach of the innovator network (IN) in order to explain if knowledge spillovers that are distributed via connections among inventors influence the success of a new venture if this venture has been founded by a person which is connected to this network. INs can be defined as networks that are built up by actors which cooperatively engage in the creation of new ideas and then economize the results (Cantner and Graf 2007). This economization can be realized within an existing firm or by the formation of a new venture. It is assumed that if a new venture is connected to a well-functioning IN, knowledge spillovers may result in new ideas, promoting firm's success.

Two data bases are used. First, patent data delivers the innovator network for Thuringia. The second data base we use contains information on innovative ventures founded in the period between 1990 and 2006, drawn from the register for commercial and private companies in Thuringia. Both data sources were merged by the names of inventors and founders.

We conduct our analysis in three steps. First we use survival analysis in order to explain the relation between a firm's innovativeness and its survival. In a second step, we look at the connection to the innovator network and its influence on a firm's innovativeness. In the third and last step, we analyse in how far the combination of innovative and connected to the network influences survival.

The remainder of the paper will proceed as follows. In Section 4.2 we will provide an overview on the mechanisms that are connecting innovator networks with entrepreneurial success and we will formulate hypotheses based on these considerations. Section 4.3 is devoted to the description of the database and methods used. In section 4.4, we present the results and provide conclusions. Section 4.5 discusses the contribution of our paper.

4.2 Innovation, new ventures and the innovator network

In evolutionary economics the emergence and diffusion of innovation is seen as the most important driver of economic change (Pyka 1999). Economic change in this context means a selection process where firms having competitive advantages as compared to the rest of the industry over time gain market shares while the other firms lose. The resource based view of the firm sees the individual characteristics of a firm as most important resources to gain competitive advantages (Penrose 1959). One kind of individual characteristic is a firm's knowledge base which is an important prerequisite for innovation. Therefore, in general the ability of a firm to generate innovation is generally seen as a key driver for economic success of firms. This relation has been empirically proven by several authors. Jaffe (1986) was one of the first to empirically show that there is a systematic relationship between firms' patents, profits and market value to the technological position of firms' research programs. In a more recent study, Hall and Bagchi-Sen (2002) show for firms in the Canadian biotech industry that R&D intensity correlates with patent measures, while innovation measured in terms of new product introductions is associated with business performance. To mention one more, Steward Thornhill (2006) has shown that innovative firms are likely to enjoy revenue growth, irrespective of the industry in which they operate and that firm knowledge, industry dynamism and innovation interact in the way they influence firm performance. Based on this reasoning, we formulate a first hypothesis:

Hypothesis 4-1 – Innovation and survival:
Innovative firms have better chances to survive the selection process of the market than non-innovative ones.

As it has been pointed out in the introduction, innovation requires a recombination of different pieces of already existing knowledge (Cantner and Meder 2007) which creates new knowledge. Since these pieces may not be in the immediate reach of a firm (Cowan et al. 2006), access to external knowledge may be an important prerequisite for innovative success. Therefore, the creation of innovation requires knowledge spillover-producing interaction.

Cassia et al. (2009), as well as Audretsch and Lehmann (2005), see university-based knowledge spillovers as the most important form of knowledge spillovers. They argue that knowledge from universities flows in the economic system and affects firms' propensity to create new market opportunities and introduce new ideas in the market. Cassia et al. (2009) as well as Audretsch and Lehmann (2005) have shown that a university's knowledge spillovers have a positive influence on firm's growth (measured as sales respectively as number of employees). Besides university-based knowledge spillovers, also spillovers from firm-researchers and employees of research institutes may play an important role since this knowledge may be more applied and ready for the market.

As stated above, knowledge spillovers are an important device for the generation of innovations and they are mainly transferred via personal contacts. In their seminal works, Breschi and Lissoni (2006) comprehensively elaborated this process. They argue that pure spillovers can only take place by trade-unrelated personal communication or through reverse engineering (Breschi and Lissoni 2006). However, when tacitness of knowledge plays a role, knowledge spillovers are not possible anymore without active participation of the inventor. As to the question why inventors should accept to pass information deliberately, Breschi and Lissoni (2006) find the answer in 'social obligations'. University researchers for example obey to the principles of open science and dedicate themselves to the production of public goods. Also corporate researchers may be willing to provide their colleagues with free advice as long as it happens reciprocally. Regarding tacitness as an important characteristic of newly generated knowledge, one could think of knowledge as a club good. Outsiders, defined as actors that are not connected to the social network of innovators, can be excluded from consuming the knowledge while insiders, defined as actors that are connected to the social network of innovators, profit from non-rivalry in the consumption of the shared knowledge.

Such a social network can be defined as innovator network (IN) that is built up by actors which cooperatively engage in the creation of new ideas and then economize the results in the market - either within an existing firm or by the formation of a new venture (Cantner and Graf 2007, Balconi et al. 2004). Innovative actors building the IN are employees of firms, of research institutes or of universities, students or self-employed persons who actively conduct research. These research oriented relationships indicate knowledge transfers and exchanges respectively knowledge spillovers which forms the basis for new ideas facilitated by the recombination of existing knowledge (Edwards and Gordon 1984). However, its not just their innovative effort which brings them together. Moreover, they get into contact by different means. They may of cause be partners in formal research cooperations between several firms. Additionally, they may be former colleagues, thus innovator mobility may play a role. It can also not be excluded that they may know each other from playing tennis in the same sports club, eating in the same restaurant or from bringing their little ones to the same nursery.

For a firm that employs an actor who is socially connected to the innovator network, the connection to the IN promotes the expansion of its knowledge base and its potential to innovate. Consequently an actor who is connected to the IN can provide an important prerequisite for the generation of innovations and therefore it may serve as an important facilitating device for long term firm survival of a firm (Thornhill 2006).

Summing up these considerations, we formulate Hypotheses 4-2 and 4-3 as follows:

Hypothesis 4-2 – Innovator network and innovative output:
Firms that are connected to the innovator network are more innovative than non-connected ones.

Hypothesis 4-3 - Innovator network and survival:
Innovative firms survive longer than non-innovative firms and this effect is driven by the connection to the innovator network.

In order to test hypotheses 4-1 to 4-3, we have created a biographical firm database which will be presented in the following section.

4.3 Database and variables

Database

In this paper we try to find out whether the social connection to the innovator network influences firms' survival. To answer this question we have constructed a biographical firm dataset, based upon two data bases. First, we use data on incorporations of enterprises in Thuringia which is based on the commercial register and second, we use patent data comprising all German patents applied for at the German Patent Office in the time period between 1993 and 2004.

Incorporations

Information on new ventures was collected by the Thuringian Founder Study[7]. The data base was drawn from the commercial register for commercial and private companies in Thuringia and contains information on the founders (date of birth, name, surname, academic title, address, gender) and on the firms (date of founding, date of closing, trade name, location, legal form, spin-off or not, industry). The survey population consists of 12,505 founders whose 7,016 companies were founded between 1990 and 2006 and are either active or have failed meanwhile. After we have cleaned the data (exclusion of firms founded before 1993 since the German reunification came with a phase of many man-

[7] Note that this data base was just the starting point for the Thuringian Founder Study Questionnaire. It is therefore not identical to the questionnaire data collected by the Thuringian Founder Study.

agement buyouts of former state combines, exclusion of firms where the founding date was missing, extraction of only those firms that are active in innovative industries following the classification of Grupp et al. (2000) a population of 4568 companies left for our investigation.

Innovator Network

Per definition, the innovator network comprises persons who cooperatively engage in the creation of new ideas and then economize the results (Cantner and Graf 2007). Both aspects have to be elaborated further. First, to be cooperatively engaged in the creation of new ideas does not necessarily mean being involved in active research cooperation. Rather it means that people may also be in the same sports club, meet each other in the same bars or restaurants, are former colleagues, have met on a conference/trade fair or take their little ones to the same nursery. The pivotal role in this respect comes to the fact that people are in contact. Also in a bar or in a sports club people talk about their jobs. Besides private information, they exchange information on what they are working on, what some colleagues of them are doing, what they have read about or what projects they are working on. This information must not be specifically related to innovative activities but at least these contacts lead to know-who respectively knowledge of who may be able to help you solving a certain problem. The underlying assumption of our approach is that a firm which is founded by one or more persons has access to the social capital of exactly these contacts they bring with. If it's not new influences for innovative activities, then this social capital at least helps to find an appropriate contact person for solving (also technical) problems. Of cause, it would also be possible to find appropriate contact persons at the internet but face-to-face contacts and personal acquaintances are an important feature since members of social networks who personally know each other tend to exchange more information, help or advice (Breschi and Lissoni 2006). Measuring these kinds of relationships of cause is impossible. In order to picture the innovator network, at least in the form of linkages that arise from the participation in a common team of inventors, we use patent data. In the same line of thinking as Breschi and Lissoni (2006), we assume that inventors who worked together on the same patent know each other well enough to be willing to exchange information and to tolerate that this information may be passed on to somebody else

than the receiver. Since those networks include members of various companies, circulation of knowledge across companies can be expected.
Second, there is the aspect of economization. This aspect restricts the network to those persons who develop new products or processes for their own firm or for their employer. They may be researchers, technologists or engineers whose aim is to create marketable ideas respectively innovations. Of cause, if we measure patent networks, we do not know whether these patents will end in a new product or process and there is no information available about how the invention has been pursued. However, since a patent application protects the knowledge from usage by other actors, it signals an intention to further use it for example in order to generate an innovation which per definition is the economization new ideas.

For this study, we constructed the inventor network of Thuringia by including all patent applications to the German Patent Office between 1993 and 2004 on which at least one Thuringian inventor (the assignment was made by postal codes of inventors' address) was listed. The resulting data base contains information on 6,969 inventors (name, surname, address) and 5,381 patent applications (IPC-Code, name and address of the applicant, application date and year). The number of inventors results after checking raw data for misspelling of personal names. Using this data set, we have constructed the one-mode affiliation network of inventors, where the connection is based upon co-inventions. The information resulting from an analysis of the network of inventors can be effectively combined with other sources of information (Balconi et al. 2004) - in our case with the firm database.

Combination of both

The combination of information gained from the innovator network with our firm database has been conducted by matching names of firm founders with names of inventors in our innovator network. It must be pointed out that this approach does not come without bias. However, we tried to check for addresses and birth dates in order to make the matches more accurate. If one or more founders of a firm are listed as inventor on a patent with an application date later than the date of firm founding, then in a first step, we counted this firm to be innovative. Sure, we here assume what we cannot observe, namely

that the founder intends to economically exploit his invention within his own firm rather than selling licences or leaving the exploitation to the applicant.
If a firm is identified as being innovative in the sense of having patents, it must not necessarily be connected to the (regional) innovator network. In a second step, we therefore created an attribute dataset, identifying inventors which at the same time have incorporated a firm. We then applied network analysis in order to distinguish between connected and isolated inventor-founders. Of cause, if a firm was founded by more than one inventor-founder it is counted to be connected as soon as at least one founder is not isolated.

The information we received from the analysis of the innovator network is used in order to create the core variables of our analysis. The variables will be presented in more detail in the following section.

Variables

Table 4-1 reports descriptive statistics for the data base we've created. Tables 4-2 and 4-3 show the correlations of the variables on a significance level of 5%.

Dependent variables

The *Survival* of a firm is its life span from the year of founding on up to the year of closing in the case the firm failed. Since we can only observe firms until the year 2006 for those firms that lived longer, we do not observe whether they failed or not after 2006. The Cox-proportional hazards model which will be described in more detail in chapter 4.4, accounts for this truncation problem of survival data.

The variable *No.Patents* counts the number of patents the firm's founder(s) applied for during the life span of the firm. This number ranges between 0 and 47 while the majority of firms (4,267 out of 4,568) count a zero.

InnoConn is a binary variable indicating whether the founders of innovative firms are connected to the innovator network (InnoConn=1; 192 out of 516 firms with innovative founders either before or after founding the firm) or whether they are isolated notes of the net (InnoConn=0; 324 out of 516 firms with innovative founders either before or after founding the firm). As we have argued above, we assume for young and small firms, that social scientific capital of the founders can be directly translated into social scientific capital of the firm. Since social relations usually do not break up from one year to the other, we also encounter the connection of the founder(s) to the network in the years before firm founding as part of the scientific social capital of the firm.

Independent variables

The variable *Innovative* is a binary variable, which measures whether the founders of the firm have applied for patents (Innovative=1; 516 out of 4568) or not (Innovative=0; 4,052 out of 4,568) before and after the firm has been founded. This indicated whether we can consider the firm to be innovative or not.

Connected is a binary variable indicating whether the founders of a firm are connected to the innovator network (*Connected*=1; 192 out of 516 innovative firms) or whether they are isolated notes of the net (*Connected* =0; 324 out of 516 innovative firms). As we have argued above, we assume for young and small firms, that social scientific capital of the founders can be directly translated into social scientific capital of the firm. Since social relations usually do not break up from one year to the other, we also encounter the connection of the founder(s) to the network in the years before firm founding as part of the scientific social capital of the firm.

*PatExperienc*e is a count variable, indicating how many patents the founders of a respective firm have applied for before founding it. For the 516 innovative firms in the sample, this variable ranges between 0 and 26. For 213 firms, we find a 0 which means that for them, we find no patenting experience. The founder(s) of the other 303 firms bring along experience in patenting.

Table 4-1 Variables used for analyzing the relationship between innovator networks and new ventures' success

	Variable	Description	Obs	Mean	Std. Dev.	Min	Max
H4-1	*Innovative*	Binary variable, indicating whether the founders of the respective firm have applied for patents (1) or not (0).	4,568	0.11	0.32	0	1
H4-2	*No.Patents*	Count variable, indicating the number of patents the founders of the respective firm have applied for.	4,568	0.21	1.48	0	47
	Connected	Binary variable, measuring for those firms of founders who have applied for patents, whether they are connected to the innovator network or isolated from it.	516	0.37	0.48	0	1
	PatExperience	Count variable, indicating the number of patents the founders of the respective firm have applied for before the firm has been founded.	516	1.83	3.24	0	26
H4-3	*InnoConn*	Binary variable indicating that an innovative firm is connected to the network (1) or isolated from it (0).	516	0.37	0.48	0	1
	Prob(InnoConn)	Probability for a firm to be innovative and connected to the network at the same time, dependent on certain individual characteristics.	4,494	0.04	0.12	0	0.97
Controls	*ABG*	Dummy for Altenburg.	3,508	0.03	0.18	0	1
	GGrz	Dummy for Gera/Greiz.	3,508	0.07	0.26	0	1
	JShk	Dummy for Jena/Saale-Holzland-Kreis.	3,508	0.12	0.33	0	1
	SOK	Dummy for Saale-Orla-Kreis.	3,508	0.02	0.15	0	1

Table 4-1 continued

	Variable	Description	Obs	Mean	Std. Dev.	Min	Max
Controls	*SaalRud*	Dummy for Saalfeld/Rudolstadt.	3,508	0.04	0.21	0	1
	Central	Dummy for Central Thuringia (Sömmerda, Erfurt, Weimar, Weimarer Land, Ilm-Kreis, Gotha).	3,508	0.33	0.47	0	1
	Sonne	Dummy for Sonneberg.	3,508	0.03	0.18	0	1
	Schmalle	Dummy for Schmalkalden/Meiningen.	3,508	0.14	0.35	0	1
	EAWak	Dummy for Eisenach/Wartburgkreis.	3,508	0.08	0.26	0	1
	UHK	Dummy for Unstrut-Hainich-Kreis.	3,508	0.03	0.17	0	1
	Eichs	Dummy for Eichsfeld.	3,508	0.04	0.19	0	1
	ShareStudents	Share of students in the whole population of the region the firm is located at.	3,508	0.02	0.04	0	0.12
	Meanturb	Mean of industry turbulence in the time span of three years before the firm has been founded and the three years afterwards.	2,900	3.96	6.64	-4.87	23.24
	Capcomp	Binary variable indicating whether the firm is a capital company (1) or a private company (0).	4,568	0.93	0.26	0	1
	Academics	Number of founding-team members that is holding an academic degree.	4,560	0.12	0.39	0	9
	Spinoff	Binary variable identifying academin spin-offs (1).	4,568	0.02	0.15	0	1
	No.Founders	Team size. Number of persons that have founded the firm.	4,560	1.39	0.77	0	16

Table 4-2 Correlations used for analyzing the relationship between innovator networks and new ventures' success – full sample (2,199 Observations; Estimations in Table 4-4 and 4-7)

		1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*
1	*Innovative*	1								
2	*Prob(InnoConn)*	0.9094*	1							
3	*ABG*	-0,0097	-0,0158	1						
4	*GGrz*	-0,0225	-0,0188	-0.0503*	1					
5	*JShk*	0.1256*	0.0457*	-0.0680*	-0.1047*	1				
6	*SOK*	-0,0263	-0,0288	-0,0285	-0.0438*	-0.0593*	1			
7	*SaalRud*	0.0348*	0.0350*	-0.0390*	-0.0600*	-0.0812*	-0.0340*	1		
8	*Central*	-0,0069	0.0387*	-0.1268*	-0.1952*	-0.2639*	-0.1105*	-0.1513*	1	
9	*Sonne*	0,0025	0,0050	-0.0333*	-0.0512*	-0.0693*	-0,0290	-0.0397*	-0.1292*	1
10	*Schmalle*	-0.0332*	-0,0283	-0.0726*	-0.1117*	-0.1511*	-0.0633*	-0.0866*	-0.2817*	-0.0739*
11	*EAWak*	-0,0309	-0.0380*	-0.0518*	-0.0797*	-0.1078*	-0.0451*	-0.0618*	-0.2009*	-0.0527*
12	*UHK*	-0,0229	-0,0206	-0,0322	-0.0496*	-0.0671*	-0,0281	-0.0384*	-0.1250*	-0,0328
13	*Eichs*	-0.0372*	-0,0260	-0.0352*	-0.0541*	-0.0732*	-0,0307	-0.0420*	-0.1365*	-0.0358*
14	*ShareStudents*	0.1250*	0.0457*	-0.0813*	-0.0748*	0.9978*	-0.0709*	-0.0971*	-0.2613*	-0.0828*
15	*Meanturb*	-0.0645*	-0.0732*	0.0432*	0.0566*	-0,0056	0,0022	-0,0385	0.0728*	0,0193
16	*Capcomp*	0,0195	0,0129	0,0027	0,0058	0,0281	-0,0050	-0,0183	0,0122	-0,0183

*p<=.05

Table 4-2 continued

		10	*11*	*12*	*13*	*14*	*15*	*16*
10	*Schmalle*	1						
11	*EAWak*	-0.1150*	1					
12	*UHK*	-0.0716*	-0.0511*	1				
13	*Eichs*	-0.0781*	-0.0557*	-0.0347*	1			
14	*ShareStudents*	-0.1703*	-0.0993*	-0.0802*	-0.0876*	1		
15	*Meanturb*	-0.0504*	-0.0691*	-0.0431*	-0.0478*	-0,0024	1	
16	*Capcomp*	-0,0074	-0,0051	0,0130	-0.0386*	0,0292	0.0454*	1

*p<=.05

Table 4-3 Correlations used for analyzing the relationship between innovator networks and new ventures' success - Sub sample (442 Observations; Estimations in Table 4-5 and 4-6))

		1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*
1	*No.Patents*	1								
2	*Connected*	0.1920*	1							
3	*PatExperience*	0.1457*	0.2275*	1						
4	*InnoConn*	0.1920*	1.0000*	0.2275*	1					
5	*ABG*	-0,0096	0,0174	-0,0465	0,0174	1				
6	*GGrz*	-0,0193	0,0780	-0,0208	0,0780	-0.0503*	1			
7	*JShk*	0.0540*	-0.1194*	-0,0240	-0.1194*	-0.0680*	-0.1047*	1		
8	*SOK*	-0,0187	-0,0892	-0,0386	-0,0892	-0,0285	-0.0438*	-0.0593*	1	
9	*SaalRud*	0,0059	-0,0629	0,0034	-0,0629	-0.0390*	-0.0600*	-0.0812*	-0.0340*	1
10	*Central*	0,0220	0.3816*	0,0854	0.3816*	-0.1268*	-0.1952*	-0.2639*	-0.1105*	-0.1513*
11	*Sonne*	-0,0024	-0,0648	0,0347	-0,0648	-0.0333*	-0.0512*	-0.0693*	-0,0290	-0.0397*
12	*Schmalle*	0,0000	-0.1599*	-0,0510	-0.1599*	-0.0726*	-0.1117*	-0.1511*	-0.0633*	-0.0866*
13	*EAWak*	-0,0250	-0,0579	-0,0517	-0,0579	-0.0518*	-0.0797*	-0.1078*	-0.0451*	-0.0618*
14	*UHK*	-0,0192	-0.1097*	-0,0208	-0.1097*	-0,0322	-0.0496*	-0.0671*	-0,0281	-0.0384*
15	*Eichs*	-0,0279	-0,0328	0,0751	-0,0328	-0.0352*	-0.0541*	-0.0732*	-0,0307	-0.0420*
16	*ShareStudents*	0.0533*	-0.1166*	-0,0240	-0.1166*	-0.0813*	-0.0748*	0.9978*	-0.0709*	-0.0971*
17	*Academics*	0.1793*	0.1290*	0.1008*	0.1290*	-0.0350*	-0,0174	0.1590*	-0.0432*	-0.0433*
18	*Spinoff*	0.0559*	0.1000*	0,0575	0.1000*	-0,0106	-0.0402*	0.0842*	-0,0266	-0.0364*
19	*No.Founders*	0.0841*	0,0620	0,0427	0,0620	0,0141	-0,0086	0.1168*	-0,0078	-0,0254

*p<=.05

Table 4-3 continued

		10	*11*	*12*	*13*	*14*	*15*	*16*	*17*	*18*	*19*
10	*Central*	1									
11	*Sonne*	-0.1292*	1								
12	*Schmalle*	-0.2817*	-0.0739*	1							
13	*EAWak*	-0.2009*	-0.0527*	-0.1150*	1						
14	*UHK*	-0.1250*	-0,0328	-0.0716*	-0.0511*	1					
15	*Eichs*	-0.1365*	-0.0358*	-0.0781*	-0.0557*	-0.0347*	1				
16	*ShareStudents*	-0.2613*	-0.0828*	-0.1703*	-0.0993*	-0.0802*	-0.0876*	1			
17	*Academics*	0.0451*	-0,0154	-0.0522*	-0.0593*	-0,0207	-0,0172	0.1603*	1		
18	*Spinoff*	0.0814*	-0,0310	-0,0174	-0.0483*	-0,0301	-0,0328	0.0841*	0.0722*	1	
19	*No.Founders*	0,0209	-0,0305	-0.0339*	-0.0345*	-0.0408*	-0,0274	0.1175*	0.3006*	0.0934*	1

*p<=.05

Prob(InnoConn) measures the probability of a firm to be connected to the innovator network and at the same time to be innovative (which means that the founders have applied for patents before or after the firms has been founded). This variable becomes zero for all firms that have no connection to innovative activities that might be measurable through patent information. For all the other firms where the founders have shown patenting activities, even before the firm has been founded, it takes a value between 0 and 1.

Control Variables

In order to control for regional differences, we created dummies for the 12 Thuringian travel-to-work areas as defined by Granato and Farhauer (2007). Figure 1-1 illustrates these areas.

The probability to be an innovative firm might differ dependent on whether a region is a so called student-region or not. Therefore, the variable *ShareStudents* measures the share of students in a travel-to-work area compared to the whole population in this area.

The firms in the sample are active in different industrial sectors and of cause the sector plays an important role to for the survivability of a firm. Since we are analyzing young firms, we decided to not only control for sectors but to also consider the economic environment/stage of the sector they are active in. For this purpose, we used data from the IAB (Institut für Arbeitsmarkt- und Berufsforschung) which contains the number of firm founding and closing for each industry (Nace 2-digit level) for the years 1976 to 2010. Based on this data, we created a variable named *Meanturb*, which is measuring the turbulence in the sector the firm is active in for a time span of six years, three years before the firm has been founded and three years afterwards. The turbulence is measured as number of firm founding in a certain sector in the specific years minus the number of firm close downs in the same sector in the same years. From this value, we take the mean over the six years around the firm founding.

In order to control whether the firm is a private company, we use the variable *Capcomp* (1 of it is a capital company, 0 otherwise).

Academics measures the number of team member that is holding an academic degree.

Spinoff measures whether the firm is an academic spin-off, which means a spin-off from a university or research institute (*Spinoff*=1) or not.

No.Founders measures the founding team's size.

4.4 Method

Innovation and survival

In order to analyze the role an innovator network plays for the survivability of a young and innovative firm, we proceed in three steps. The first step is to identify the relation between innovativeness and survival of a firm. Since in this first step success is measured in terms of survival, we apply Cox's proportional hazards model (1972). It has been widely recognized that survival as an outcome variable does not come without bias. The problem arises due to non-complete measurements on all 'members' or entities of a random sample (Kaplan and Meier 1958). For example in medical follow-up studies, contact to some of the individuals will be lost before their death and others will die due to other reasons. Similarly the observation of the lifetime may be ended at a certain point in time, due to the need to get out a report within a reasonable time. In many applications, and this holds also for our investigation, survival may be a subject to right censoring and left truncation (Tsai et al. 1987). Right-censored cases are study objects whose failure event is not observed. The term "right-censored" implies that the event of interest is to the right of our data point (Kaplan and Meier 1958). In other words, if the units were to keep on operating, the failure would occur at some time after our data point. Truncation is a source of bias in survival analysis, in which certain objects are ignored and not sampled (Tsai et al. 1987). Left-truncation occurs when some subjects are registered at a delayed time. Our database contains firms founded at several points in time. Thus, we have a problem with left-truncation. We also cannot observe the event of interest (closure) for some of our observations, thus we also have right-censored data. We use the Cox proportional hazards model

(1972) since it gives a valid estimate of the survival rate for data sets including right-censored and left truncated cases.

Innovator network and innovative output

After having identified the relation between innovativeness and survival, we are devoted to analyse in a second step the relation between the connection to the innovator network and innovativeness. This means that we ask whether in the group of innovative firms those with connection to the innovator network are more successful in innovating than the isolated ones. Since the number of patents applied for as our outcome variable is highly skewed to the left with a high number of zeros, we apply negative binomial regression as proposed by Greene (2003) as well as Cameron and Trivedi (2013).

Innovator network and survival

The third step of the analysis aims on bringing together the first two steps. We want to see whether the combination of being innovative and connected to the network influences firm survival. In order to do this, we first analyse the factors that explain this aforementioned combination. This means that we regress special characteristics on the binary variable *InnoConn*. Since the outcome variable is binary, we use logistic regression for this. The individual coefficient of this regression (the fitted value), tells us for each firm that is at least innovative, the probability to be innovative and connected at the same time based on certain characteristics. This value is stored and in the next step, we use it as explanatory variable for the survivability of the firm in a cox regression.

4.5 Empirical Results

Innovation and survival

Table 4-4 shows the results for the first step of analysis which is devoted to hypothesis 4-1 stating that innovative firms have better chances to survive the selection process of the market than non-innovative ones.

Models 1-3 differ in the inclusion of regional control variables. Considering all three models, we find that the coefficient for the dummy variable *Innovative* ranges between 0.64 and 0.76 on a 1-10% significance level. This means that innovative firms have a risk to die in the upcoming period which is only about

70% of the risk for non-innovative firms. Therefore, hypothesis 4-1 cannot be rejected.

Innovator Network and innovative output

The second step of analysis is devoted to the second hypothesis which is assuming that innovative firms that are connected to the innovator network show a higher innovation output than isolated ones. The causality however, appears to stay unclear. It might be that case that firms apply for more patents since they are connected to the innovator network. But it might as well be true that the highly innovative firms are connected since they have more patents. We do not claim to have an answer to this point here. The models just aim at revealing the connection in our data. The question which direction is the true one remains unsolved. Table 4-5 shows the results of our negative binomial regression on the number of patents a firm applied for in four models which differ with respect to the inclusion of control variables.

Over all models, the relationship between the connection to the innovator network and the number of patents a firm applies for is significant and positive. Interpreting model 4, we find that, all the other variables considered being constant, the connection to the innovator network increases the differences in the logs of the patent count by 0.59 units. Therefore, we cannot reject hypothesis 4-2 and assume that the innovator network has a positive influence on the degree of innovativeness in the group of innovative firms.

Table 4-4 The influence of innovativeness on the hazard ratio

Method	Cox regression - Breslow Method for ties					
Dep. Var.	survival					
Population	all firms					
	model 1		model 2		model 3	
Innovative	0.7568	*	0.7015	**	0.6433	***
	(-1.66)		(-2.09)		(-2.59)	
ABG					6.0795	***
					(4.53)	
GGrz					5.3627	***
					(4.59)	
JShk			1.4725	***	4.7279	***
			(2.85)		(4.39)	
SOK					4.7730	***
					(3.60)	
SaalRud					6.2421	***
					(4.79)	
Central			0.4627	***	1.4790	
			(-5.61)		(1.10)	
Sonne					3.1264	***
					(2.76)	
Schmalle					4.1954	***
					(4.06)	
EAWak					0.5847	
					(-1.02)	
UHK					1.3157	
					(0.49)	
Eichs					1.0088	
					(0.02)	
Capcomp	0.7404	*	0.7105	**	0.7113	**
	(-1.75)		(-1.98)		(-1.97)	
Meanturb	1.0351	***	1.0387	***	1.0340	***
	(5.00)		(5.52)		(4.77)	
No. of Obs.	2,199		2,199		2,199	
No. Of Failures	367		367		367	
Prob>Chi2	0.000		0.000		0.000	

Robust z statistics in parentheses

*significant at 10%, **significant at 5%, ***significant at 1%

Table 4-5 The influence of being connected to the innovator network on the number of patents an innovative firm applies for

Method	Negative binomial regression							
Dep. Var.	*No.Patents*							
Population	all firms							
	model 1		model 2		model 3		model 4	
Connected	0.5164	***	0.5013	***	0.5543	***	0.5955	***
	(3.23)		(3.16)		(3.15)		(3.31)	
PatExperience			0.0434	**	0.0377	*	0.0302	
			(2.09)		(1.81)		(1.45)	
ABG							2.6978	**
							(2.25)	
GGrz							0.8015	
							(1.52)	
JShk					6.2492		-24.3060	*
					(1.55)		(-1.89)	
SOK							2.1660	
							(1.63)	
SaalRud							2.6545	**
							(2.32)	
Central					-0.1042		1.7021	**
					(-0.53)		(2.13)	
Sonne							2.8368	**
							(2.41)	
Schmalle							2.9570	***
							(2.90)	
EAWak							1.5311	**
							(2.01)	
UHK							2.2234	*
							(1.78)	
Eichs							omitted	
Academics	0.4409	***	0.4130	***	0.4576	***	0.4617	***
	(3.48)		(3.27)		(3.54)		(3.54)	
Spinoff	-0.1214		-0.2315		-0.1827		-0.1730	
	(-0.47)		(-0.88)		(-0.68)		(-0.66)	
No.Founders	0.1024		0.1115		0.0978		0.0900	
	(1.05)		(1.15)		(1.01)		(0.93)	
ShareStudents	1.0681		1.6061		-51.9694		225.9738	*
	(0.71)		(1.06)		(-1.51)		(1.94)	
Constant	-0.0089		-0.1106		0.0695		-2.7225	**
	(-0.05)		(-0.59)		(0.32)		(-2.43)	
No. of Obs.	442		442		442		442	
Pseudo R2	0.0266		0.0295		0.0312		0.0412	

Robust z statistics in parentheses
*significant at 10%, **significant at 5%, ***significant at 1%

Innovator network and survival

In order to test hypothesis 4-3, we start by calculating the individual probability of a firm to be innovative and connected to the innovator network at the same time (*Prob(InnoConn)*). Table 4-6 shows the logistic regression for this.

Table 4-6 Variables that are determining the probability for a firm to be innovative and connected to the innovator network at the same time

Method	Logistic regression	
Dep. Var.	*InnoConn*	
Population	all firms	
	model 1	
PatExperience	0.1560	***
	(4.19)	
Academics	0.5708	***
	(3.04)	
Spinoff	0.8551	**
	(2.42)	
No.Founders	0.1113	
	(0.8)	
ShareStudents	-7.2862	***
	(-3.11)	
Constant	-1.1191	***
	(-4.20)	
No. of Obs.	442	
Pseudo R2	0.0851	

Robust z statistics in parentheses
*significant at 10%,**significant at 5%,
***significant at 1%

The probability to be connected and innovative, which can only be calculated if the firm is indeed innovative and connected, depends on the firm's experience in patenting (*PatExperience*), the number of academics in the team (*Academics*) , whether the firm is a spin-off (*Spinoff*) and the share of students among the whole population in the region (*ShareStudents*). For all firms where, *InnoConn* is 0, we set

Table 4-7 Influence of the probability to be innovative and connected to the innovator network on the hazard ratio

Method	Cox regression - Breslow Method for ties					
Dep. Var.	survival					
Population	all firms					
	model 1		model 2		model 3	
Prob(InnoConn)	0.4851	*	0.4784	*	0.3796	**
	(-1.68)		(-1.65)		(-2.14)	
ABG					6.0375	***
					(4.51)	
GGrz					5.3268	***
					(4.57)	
JShk			1.4329	***	4.5649	***
			(2.67)		(4.30)	
SOK					4.7659	***
					(3.60)	
SaalRud					6.1765	***
					(4.76)	
Central			0.4646	***	1.4817	
			(-5.58)		(1.11)	
Sonne					3.1189	***
					(2.76)	
Schmalle					4.1853	***
					(4.05)	
EAWak					0.5820	
					(-1.03)	
UHK					1.3085	
					(0.48)	
Eichs					1.0124	
					(0.02)	
Capcomp	0.7402	*	0.7098	**	0.7105	**
	(-1.75)		(-1.99)		(-1.98)	
Meanturb	1.0351	***	1.0390	***	1.0343	***
	(5.00)		(5.56)		(4.81)	
No. of Obs.	2,199		2,199		2,199	
No. Of Failures	367		367		367	
Prob>Chi2	0.000		0.000		0.000	

Robust z statistics in parentheses
*significant at 10%,**significant at 5%,
***significant at 1%

Prob(InnoConn) to 0 which means that we here do not use the fitted but the real value in order to explain whether the connection to the innovator network is positively linked to the survivability of firms. In order to do this, we use Cox proportional hazards model and explain survival with the probability to be connected to the innovator network and innovative as well as some control variables. Table 4-7 shows the results.

Again, models 1-3 differ simply in the inclusion of control variables. If we look at our main variable of interest, *Prob(InnoConn)*, we can see that a high probability to be innovative and connected to the innovator network reduces the hazard ratio to about 48%.
Therefore, we cannot reject hypothesis 4-3 and assume that the connection to the innovator network plays an important role in the explanation of differences in the survival of firms.

4.6 Discussion and conclusions

The aim of this paper was to show for young firms in innovative industries in how far the connection to the innovator network or in other words, the amount of scientific social capital the firm can make use of, is a hub for its chances to survive the economic selection process.
In a first step, we looked at the factors that influence innovativeness and find the connection to the innovator network to be one of the main ones. However also experience in patenting positively influences whether the founders of the respective firm go on with their patenting activities. Additionally the number of founders with academic background positively influence tendency of a firm to apply for patents.
In the next step, we looked at the connection between innovativeness, the innovator network and the survivability of firms. The theoretical framework suggested that this relation is positive and that an innovative firm which is connected to the innovator network has more success in gaining competitive advantages through innovation and therefore has better chances to survive. An analysis of 4,568 companies in the German state Thuringia indicates that the probability of a firm to be innovative and connected to the innovator network at the same time is positively related to its probability to survive.

Besides the connection to the innovator network, three other factors turn out to be influential for the viability of a young company. We find that capital companies have a reduced hazard ratio as compared to private companies.

The mean turbulence of the industry the firm is active in for the time span three years before and three years after firm founding is negatively related to the hazard ratio. A high value of turbulence indicates a recently growing sector where there are more company founding's than closings. According to Gort and Klepper's (1982) theory on the diffusion of product innovations (Industry Life Cycle), this industry is in phase II which is the interval from the take-off point of the net entry until the net entry starts to decline drastically. This explains the negative connection which we find for the survival of firms. If a firm is founded in phase II it has to go through phase IV which is a phase of shake out where the net entry becomes negative and where many firms are closed until the market stabilizes. The probability that a firm does not survive this stage is quite high which goes in line with what we find in our data.

We also find that survival differs regionally. With respect to firm's survival and success, location has been identified as one among many critical factors (Heckmann and Schnabel 2005, Storey 1994). However, locations differ with respect to their organizations like universities, research institutes, firms or public agencies, as well as with respect to institutional factors like norms and regulations, a qualified labour force or business taxes. Besides these, but related, an important locational factor is the regional innovation system as defined by Cooke et al. (1997). The network of innovators can be seen as one core element of such an innovation system. However, it may not be irrelevant to which IN a firm is connected. Various researches have shown that, first, innovative activities are spatially not evenly spread but a rather regionally bounded phenomenon (Asheim and Isaksen 2002). Thus, innovative performance differs among different regional innovation systems (e.g. Porter 1990, Jaffe et al. 1993). Second, regions differ with respect to the success of their respective firms or with respect to founding rates (e.g. Storey 1994). The success of incumbent firms as well as their founding rate is driven by innovation (Nijkamp 2011, Audretsch and Lehmann 2005, Brown and Eisenhardt 1997, Lumpkin and Dess 1996) which in turn is driven by the IN. If regions differ with respect to innovative and firm performance, this may be due to different characteristics of the respective regional innovator networks (RINs). Among those characteristics may be network properties like a high degree of connectedness, a high centrality of single actors or the existence of structural holes. Additionally, one might expect differences occurring due to the characteristics of the knowledge that is flowing in the network. Some regions are highly specialized, thus concentrated on a small number of industries. In these regions, the knowledge flowing through the RIN will also be very specialized and therefore the knowledge bases of the network-actors will have a high degree of overlap. Other regions are more diverse with respect to industries. Consequently, the knowledge flowing through the network is rather diverse and the actors' knowledge bases show a low degree of overlap. These considerations leave lots of space for further research on the connection between network characteristics and firm's success.

5. The selective nature of innovator networks: from the nascent to the early growth phase of the organizational life cycle

5.1 Introduction

Over the 1990s, scholars have come to the consensus that networks play an important role for the emergence and survival of new ventures (Aldrich and Reese 1993, Larson and Starr 1993, Stuart et al. 1999). However, with regards to the evolutionary process behind firm growth and survival at different stages of the organizational life cycle (Hite and Hesterly 2001), recent interest has been devoted to the variable 'location' as a critical factor, shaping firm performance.

We elaborate the approach of regional innovator networks (RIN) which can be defined as networks that are built up by actors who cooperatively engage in the creation of new ideas and then economize the results (Cantner and Graf 2007), where the economization can be realized within an existing firm or by the formation of a new venture. In a previous study (Cantner and Wolf 2016) we found that for a new venture being simply connected to the innovator network increases the survival probability. The further step in this paper is to look at the "quality" of the network and of how a new venture is connected to the network (position in the network, relation to other actors, bridging functions). Examining the relationship between network position of the founder and survival of firms can provide both, an estimation of the role of different elements of network structure in firms' success and an empirical indicator for the effectiveness of knowledge flows through networks.

According to the propositions by Hite and Hesterly (2001), an analysis of the relationship between the selectivity of the innovator network and start-ups' survival cannot be conducted independently of the organizational life cycle status of the individual firm. Therefore, we consider three early stages in the life cycle, namely, the nascent stage, the founding stage and the post founding stage, and ask the following research question: *What role does the structure of the innovator network, the position of the founder(s) in the network and the* *structure of the founder's ego-network play for the survival of firms in the early stages of the organizational life cycle?*

To address this overarching research question, we have constructed a biographical firm dataset, based upon data on incorporations of enterprises in Thuringia as well as on patent data comprising all German patents applied for at the German Patent Office.

5.2 Organizational life cycle

In strategy and entrepreneurship research, organizational life cycles are used to explain how firms evolve through the following (mostly five) progressive stages: emergence, early growth, later growth, maturity and death (Churchill and Levis 1983, Gartner et al. 1992). These studies expect that the emergence stage of the firm, and with this it's life, begins when the organization is legally created (Gartner et al. 1992). However, as Reynolds (2000) argues, there is also an important phase before the legal founding which is the conception or nascent stage of the firm life.

In this paper, we will concentrate on the phases between nascent entrepreneurship and early growth of the firm. Throughout all the phases of a firm's life, the strategic goals, natural resource needs and acquisition challenges are changing several times (Hite and Hesterly 2001).

A nascent entrepreneur can be defined as 'someone who initiates serious activities that are intended to culminate in a viable business startup' (Aldrich 1999, p. 77). This means that in this phase, the nascent entrepreneur is experimenting with different business ideas, starts to take care of the first stages in the founding process (like writing a business plan) and starts to collect resources along with applying for financial funds. Depending on the industry/technology the start-up will be active in, the founder(s) might also start to produce first prototypes. In this phase there seems to be no real strategic orientation but the four factors entrepreneurial personality, environment, resources, and founding process comprehensively influence founding success (Kessler and Frank 2009, Cantner and Stuetzer 2013).

After the legal founding of the firm, the emergence stage begins (Gartner et al. 1992). In the emergence stage, the firm starts to act on the real market such that

one could say that after the legal founding the start-up enters in to the selective process of competition. In this phase the only strategic goal of the firm is not to die, thus to survive the selection process (Hite and Hesterly 2001). With respect to resources, these newborn firms usually lack internal resources and capabilities to reach this goal (Baum 1996). Additionally the operations of emerging firms are characterized by a high degree of uncertainty and equivocality (Gartner et al. 1992) as well as by a lower degree of legitimacy and reputation (Hite and Hesterly 2001).
If the firm enters the early growth stage, it has survived already the toughest part of the competition process, usually due to a competitive advantage. Now the firm is settled in the market and might be for the first time able to set its own conditions. Thus, when the firm enters the early growth stage it starts to make real strategic decisions and therefore requires a broader scope of resources but, however, could already gain legitimacy and reputation which reduces uncertainty (Hite and Hesterly 2001).

Organizational life cycle theory does not describe the exact time span or duration for the single phases of the life cycle. This is not surprising since the development of a firm is an individual process which differs from firm to firm. The nascent stage is usually considered to take around three years (Kessler and Frank 2009). After the legal firm founding, it is well known that survival rates are very low in the beginning due to the liabilities of newness and smallness (Parker 2009). After an initial honeymoon phase (which is the emergence stage according to the organizational life cycle theory), many small and young firms suffer from these liabilities and exit while others enter the early growth stage. Studies on the distribution of survival rates see the length of the emergence stage somewhere between five and seven years (Phillips and Kirchhoff 1989, Bartelsman et al. 2005).

Of cause along with the changes in needs for the young firms, the influence of the social (scientific) network around the founders changes. Before elaborating this, we start by describing the role of innovative networks per se.

5.3 Knowledge diffusion in regional innovator networks

We define the RIN as a network that is built up by actors, living in a certain region, which cooperatively engage in the creation of new ideas and then economize on the results in the market - either within an existing firm or by the formation of a new venture (Cantner and Graf 2007, Balconi et al. 2004). Innovative actors building the RIN are employees of firms, of research institutes or of universities, students or self-employed persons who actively engage in research (Cantner and Wolf 2016).

After we have defined the innovator network, the following question arises: How can the connection of single actors to the RIN contribute to firms' innovation? As mentioned in the definition, the RIN inherits connections among actors that are engaged in research, no matter if it is basic or applied (Cantner and Graf 2007, Balconi et al. 2004). These actors usually are experienced experts and they have current knowledge in their field. Since knowledge can be codified or tacit, acquiring new knowledge pieces may require personal contacts to other actors which possess this new knowledge (Howells 2002). Breschi and Lissoni (2006) argue that pure knowledge spillovers can only take place by trade-unrelated personal communication or through reverse engineering. However, when tacitness of knowledge plays a role, knowledge spillovers are not possible anymore without active participation of the inventor. Thus, actors that are connected to the social network of innovators will receive more new knowledge pieces than an isolated actor and they will therefore have a higher probability to find new combinations.

As pointed out: Knowledge, which is possessed by actors and transferred via the RIN, is an important prerequisite for the generation of innovations within a firm. By definition, actors connected to the RIN intend to economize their research's results (Cantner and Graf 2007). This can happen within an existing firm or by founding a new one. Thus, a firm whose employees or founders are connected to the innovator network will be more likely to be innovative than firms whose employees or founders are isolated from this network (Cantner and Wolf 2016). With respect to the creation of a new firm, the interpretation of the contribution of an entrepreneur's network to the firms' scientific knowledge base is similar to the notion by Murray (2004) but we adapt it to entrepreneurship theory. Murray (2004) investigates in how far academic scientists contribute to the firm's own scientific network by providing their scientific social capital. Our notion of the regional innovator network points to the importance of the whole research community within a region. Furthermore, we expect an entrepreneur who is connected to this regional research community (from now on, we call him networked-founder), not an academic inventor as Murray (2004) does, to bring his scientific social capital to the firm and to also intent to translate it to the firms' scientific network. This so called scientific social capital of the firm is even increased if there is more than one networked-founder (team founding). Thus, the scientific human capital of the founder(s) leads a firm to become embedded within the scientific community of the region. Scholars have argued that linkages and the resulting networks are key vehicles through which firms obtain access to external knowledge (Powell et al. 1996). The connection to such a network delivers information and it is a vehicle for the rapid communication of news about opportunities and obstacles. Thus, the generation of innovation and the recognition of new market opportunities are eased, which both are drivers of growth and survival (Audretsch 1995).

5.4 Early stages in the organizational life cycle and the evolution of firm networks

As argued above, the needs of a firm change along its life cycle and consequently the exigence to the innovator network changes over time. At the same time, the network itself evolves and changes. This is due to the process of dynamic network evolution where firms strategically adapt and align their networks to serve their needs (Golden and Dollinger 1993, Ostgaard and Birley 1994, Balland et al. 2015). This means that the individual firm changes its ego-network but, if all firms do this, naturally the whole network changes. Therefore, in contrast to Hite and Hesterly (2001) who specifically focus on the ego-centric network of the firm, we will additionally consider the structure of the whole regional innovator network as influential factor on firm success.

5.4.1 Structural issues on the diffusion of knowledge in RINs

It has been pointed out in chapter 5.3 that the connection to a regional innovator network can influence firm's innovative success and in line with this, firms'

growth and survival. If we consider start-ups, connected to the RIN, specific effects of network structures on the organizational performance may play a role. These specific effects also depend on the stage in the organizational life cycle and the related strategic needs of the firms.
Considering the nascent stage of the firm's live, Cantner and Stuetzer (2013) show that factors like start-up capital, the functional background and entrepreneurial experience of the founders seem to overweight the importance of social capital for the success of the new venture. The founders are too busy in writing the business plan, getting funds and find a niche to put their business idea in that the scientific social capital plays a less relevant role in this stage of the organizational life cycle. Therefore, we expect that the structural form of the innovator network does not influence the firm in this very early stage:

Hypothesis 5-1a:
The connectivity of the innovator network in the ***nascent stage*** *of the organizational life cycle does not influence the firms' chances to survive.*

In the emergent stage, the firm already entered into the market and started to compete with other actors in this market. In this phase, the founders need to know everything that is going on in the technological field. In highly connected networks where one finds connections between many of the actors, knowledge can flow quite fluently from one actor to the other. Gilsing et al. (2008) additionally argue that highly connected networks help to understand new knowledge adequately since partners may complement actors' absorptive capacities and they help building up trust by reputation. For example Fershtman and Gandal (2011) find for open source software projects that the success of the projects there is a positive connection to the closeness centrality of the project network. Also Meagher and Rogers (2004) prove formally that there exists a feedback between spillovers and innovation and that those industries with a greater network density have a higher proportion of innovators. Cohesive networks are characterized by high density, high mutuality among ties and a relative high frequency of ties among group members, while in sparsely connected networks, where fragmentation is quite high, only a small number of knowledge spillovers may occur (Wasserman and Faust 1994). During the emergence stage, young firms profit from better access to resources and a mutual understanding which is driven by a high degree of trust and expected future reciprocity (Hite and Hesterly 2001). Therefore, we hypothesize that:

Hypothesis 5-1b:
*Firms have higher chances to survive if the connectivity of the net their founder is connected to is high in the **emergent stage**.*

When the firm develops and enters into the early growth stage, the advantages of a very cohesive network may turn into disadvantages. First, the costs associated with maintaining contacts to many actors are quite high (Burt 1992). Second, if there are many direct and indirect ties in the net, every actor knows what the other actors know and therefore it is less likely to gain new knowledge inflows from the net (Gilsing et al. 2008). Third, there is the risk of undesired knowledge spillovers in a way that the partners of actor A's partners may receive parts of A's knowledge although A doesn't want it (Gilsing and Nooteboom 2005). Therefore, in the early growth stage, the fragmented network becomes more appropriate (Hite and Hesterly 2001). Thus, we hypothesize the following:

Hypothesis 5-1c:
*Firms have higher chances to survive if the connectivity of the net their founder is connected to is low in the **early growth stage** of the organizational life cycle.*

5.4.2 Entrepreneurs position in the RIN and knowledge flows to the firm

After we have defined in chapter 5.4.1 how the net as a whole should look like to positively contribute to the survival of the nascent and young firm, we now have a look at the founder's position in the net. Which position of a single node (networked-founder) is favourable to profit as much as possible from knowledge flows in the net? And how does this depend on the stage in the organizational life cycle?

If we look at the entrepreneurs' position in the network, we basically look at how important he is. In graph theory, centrality is a measure of how well connected or active an actor is in the overall network. Thus centrality helps meas-

uring how prominent or important single actors are in the net (Wasserman and Faust 1994). The actor with the highest centrality, is the one "where the action is" as he is the most visible actor in the network (Gilsing et al. 2008).
As argued above, in the nascent stage, factors like start-up capital, the functional background and entrepreneurial experience of the founders are the main factors, influencing firm survival (Cantner and Stuetzer 2013). Therefore, we again expect that the entrepreneurs' position in the network does not influence the chances of his chances to survive. Therefore, hypothesis 5-2a goes as follows:

Hypothesis 5-2a:
A central position of the networked-founder' in the RIN in the ***nascent stage*** *of the organizational life cycle does not influence firm survival.*

After the firm entered the market, it needs to know everything that is going on in the technological field. A networked-founder, with a high degree centrality is in direct contact or adjacent to many other actors (networked-founders or inventors) such that this founder should be recognized by others as a major channel of information. This makes it more likely for him to receive knowledge spillovers, thus information about opportunities or obstacles. Consequently, we hypothesize:

Hypothesis 5-2b:
The more central the position of the networked-founder' in the RIN in the ***emergent stage*** *of the organizational life cycle the higher are the firms' chances to survive.*

We argued above that the firms' need for a cohesive network decreases over the life cycle, due to a better control of the resource and knowledge flows between the other actors (Hite and Hesterly 2001). If we now consider the position of the founder in the network, we might expect that central actors may be comparably able to control knowledge flows and even use this position for his own purposes (Burt 1992). This then makes it more likely for the networked founder to receive and control knowledge spillovers. Therefore, we hypothesize for the early growth stage that:

Hypothesis 5-2c:
The more central the position of the networked-founder' in the RIN in the ***early growth stage*** *of the organizational life cycle the higher are the firms' chances to survive.*

5.4.3 Entrepreneurs' ego-network and knowledge flows to the firm

In social networks theory, a debate has arisen over the form of egocentric network structures that can appropriately be regarded as beneficial for connected firms (Walker at al. 1997). Coleman (1988) sees the optimal social structure of an ego network in dense and interconnected networks, while Burt (1992) sees a network consisting of disconnected alters as optimal. Also the number of direct and indirect ties may play a role for the advantageousness of a network structure (Ahuja 2000). As Hite and Hesterly (2011), we consider the optimal structure of the ego-network to change over the firm's life.

Again, the nascent stage is characterized by factors like start-up capital, the functional background and entrepreneurial experience rather than the social networks (Cantner and Stuetzer 2013). Therefore, we expect no connection between the shapes of the ego-networks within the innovator network and the success of the new ventures:

Hypothesis 5-3a:
The shape of the egocentric networks within the innovator network does not influence survival of the firm in the ***nascent stage****.*

In the emergent stage, the firm needs to be informed about everything that is going on in the technology and the related market. Therefore, an ego-network that is allowing for the highest possible amount of knowledge inflow is favourable (Hite and Hesterly 2011). According to Coleman, densely embedded networks (closed networks) with many connections and thus no or less structural holes is associated with a higher innovative output. Ahuja (2000), among other factors, investigates the relationship between the number of structural holes in the ego network of a firm and innovative outputs and finds that having many structural holes is associated with reduced innovation. Since this kind of ego-network structure is exactly what a start-up in the emergent stage needs, we hypothesize:

Hypothesis 5-3b:
*The more closed the ego-network of a networked-founder is, the higher is the survival probability of this founder's firm in the **emergence stage**.*

However, if the firm moves to the early growth stage, it rather needs an ego-network that allows a strategical use of the own position (Hite and Hesterly 2011). One characteristic of the ego-network is brokerage/structural holes (Burt 1992). Networks usually consist of one or more components. Burt defines a 'hole' / non connection between those components as structural hole. As we see nodes as actors, one could say that "people on either side of a structural hole circulate in different flows of information. Structural holes are thus an opportunity to broker the flow of information between people, and control the projects that bring together people from opposite sides of the hole." (Burt 1992). One could also say that structural holes guarantee that partners on both sides of the whole have access to different information flows (Hargadon and Sutton 1997) and the information coming from this connection is non-redundant (Gilsing et al. 2008). However, not every firm or actor has the same chance to be in a bridging position. Central firms tend to become better informed about the things happening in the network what increases their ability to form new and valuable ties (Gnyawali and Madhavan 2001, Gilsing et al. 2008). Thus, we hypothesize that:

Hypothesis 5-3c:
*The more structural holes the ego-network of the founder has, the higher are the chances to survive when the firm moves to the **early growth stage**.*

5.5 Compounding the database

To address the hypotheses introduced above, we have constructed a biographical firm dataset, based upon two data bases. First, we use data on incorporations of enterprises in Thuringia which is based on the commercial register. Second, we rely on patent data comprising all German patents applied for at the German Patent Office in the time period between 1993 and 2004.

Incorporations

Information on new ventures was collected by the Thuringian Founder Study[8]. The data base was drawn from the commercial register for commercial and private companies in Thuringia and contains information on the founders (date of birth, name, surname, academic title, address, gender) and on the firms (date of founding, date of closing, trade name, location, legal form, spin-off or not, industry). The survey population consists of 12,505 founders whose 7,016 companies were founded between 1990 and 2006 and are either active or have failed meanwhile. After we have cleaned the data (exclusion of firms founded before 1993 since the German reunification came with a phase of many management buyouts of former state combines; exclusion of firms where the founding date was missing; extraction of only those firms that are active in innovative industries following the classification of Grupp et al. (2000) which is classifying innovative industries by means of R&D-intensity) a population of 4,566 companies was left.

Innovator Network

As mentioned in the introduction, we use patent data in order to measure the innovator network. Per definition, this network comprises persons who cooperatively engage in the creation of new ideas and then economize the results (Cantner and Graf 2007). How these two aspects of creating and economizing new ideas can be combined into the innovator network and what this means for new ventures has been elaborated in more detail by the authors' earlier paper Cantner and Wolf (2016) and shall not be repeated here. To summarize the arguments of the paper mentioned one can say that patent data, which basically just contains information on inventions, is a sufficient measure of innovator networks since the aim of commercialization can be expected behind the legal protection of the invention.

We used data from the German Patent Office where we have in Thuringia 6,969 inventors (name, surname, address) and 5,381 patent applications (IPC-

[8] Note that this data base was just the starting point for the Thuringian Founder Study Questionnaire. It is therefore not identical to the questionnaire data collected by the Thuringian Founder Study.

Code, name and address of the applicant, application date and year), resulting after checking raw data for misspelling of personal names[9].

It has been found that regions differ with respect to firms' success due to different infrastructural conditions (Heckmann and Schnabel 2005, Storey 1994). Additionally, the conditions for bringing competencies into innovator networks may differ between functional regions since an innovator may find the competencies he needs easier in large and dense networks compared to smaller ones (Ejermo and Karlsson 2006). This holds especially true for large regions with a university and several research institutes. Not just that universities and research institutes are responsible for knowledge spillovers which have a positive influence on innovations (Audretsch and Lehmann 2005), it can also be expected that actors in these networks are better connected and thus better informed than those in regions without research facilities and with less dense networks (Ejermo and Karlsson 2006). On the basis of these considerations, we have created 12 one-mode-affiliation networks of innovators (RINs) according to the Thuringian travel-to-work areas[10] (ttwa) as defined by Granato and Farhauer (2007) who applied factor analysis for commuter streams.

Combination of both

The combination of the information from the regional innovator network with our firm database was done by matching names of firm founders with names of inventors in our innovator network. It must be pointed out that this approach does not come without bias. However, we tried to check for addresses and birth dates in order to make the matches more accurate. If one or more founders of a firm are listed as inventor on a patent, then in a first step, we counted this firm to be innovative. Sure, we here assume what we cannot observe, namely that the founder intends to economically exploit his invention within his own firm rather than selling licences or leaving the exploitation to the applicant. However, since a patent application protects the knowledge from usage by other actors, it signals an intention to further use it for example to generate an innova-

[9] For consistency, we used a routine which was applied to all data sets.
[10] Figure 1-1 shows a card of Thuringia and its ttwas. Sonneberg, Saale-Orla-Kreis, Altenburger Land and Eichsfeld are connected to regions outside Thuringia by means of commuter streams. For the creation of the regional innovator networks, we also included patents and inventors from these regions.

tion, which per definition is the economization of new ideas. Furthermore, every granted patent inherits a test with respect to the commercial usability of the invention. By combining both databases, we were able to identify networked-founders in the RINs and relate their network positions, properties to their firms. They are connected to the regional innovator network of the ttwa their firm is located at. As patenting is a quite rare event, we come up with a database of 149 innovative firms out of the sample population we have from the commercial register, which was 4,566 founded firms in Thuringia.

5.6 Variables and methodology

The next section is dedicated to present the variables used and the methodology applied. Table 5-1 gives a detailed overview on all variables used in the estimations; table 5-2 presents the correlations between these variables.

Table 5-1 Description of variables used in order to investigate the selective nature of innovator networks

	Variable	Description	Obs	Mean	Std. Dev.	Min	Max
Structure of the network (H1a-c)	Net_{-3}	Variable describing the density of the network three years before the firm founding.	149	0.007	1.000	-1.063	3.308
	$Net_{-3}SQ$	Net_{-3} Squared	149	0.992	2.035	0.000	10.942
	Net_0	Variable describing the density of the network in the year of founding.	149	0.001	1.003	-0.821	2.915
	Net_0SQ	Net_0 Squared	149	1.000	2.334	0.001	8.495
	Net_{+5}	Variable describing the density of the network five years after firm founding.	149	0.000	1.003	-1.043	1.622
	$Net_{+5}SQ$	$Net+_5$ Squared	149	1.000	0.931	0.000	2.631
Position of the founder (H2a-c)	EV_{-3}	Founders' eigenvector centrality three years before the firm founding.	37	-0.777	17.315	-86.497	57.735
	EV_0	Founders' eigenvector centrality in the year of founding.	149	0.000	0.001	0.000	0.009
	EV_{+5}	Founders' eigenvector centrality five years after firm founding.	149	0.019	3.276	-29.564	26.400
	MC_{-3}	Binary variable, indicating whether the firm has been connected to the main component three years before the firm founding.	149	0.007	0.082	0.000	1.000
	MC_0	Binary variable, indicating whether the firm has been connected to the main component in the year of its founding.	149	0.040	0.197	0.000	1.000

Table 5-1 continued

	Variable	Description	Obs	Mean	Std. Dev.	Min	Max
Ego-Net (H3a-c)	*MC_0*	Binary variable, indicating whether the firm has been connected to the main component in the year of its founding.	149	0.040	0.197	0.000	1.000
	$Constr_{-3}$	Constraint of the ego-network three years before the firm founding.	149	0.223	0.396	0.000	1.125
	$Constr_0$	Constraint of the ego-network in the year of its founding.	149	0.445	0.454	0.000	1.125
	$Constr_{+5}$	Constraint of the ego-network five years after firm founding.	149	0.677	0.381	0.000	1.125
Controls	*PatExperience*	Number of patents the firm founders applied for before the firm has been founded.	149	1.309	2.205	0.000	11.000
	#Patents	Number of patents the firm applied for from the year of founding on.	149	2.268	4.132	0.000	28.000
	#Founders	Number of founders in the team.	149	1.638	0.816	1.000	6.000
	Spinoff	Binary variable, indicating whether the firm is an academic spin-off or not.	149	0.195	0.397	0.000	1.000
	CapComp	Binary variable, indicating whether the firm has the legal form of a capital company (1) or a private company (0).	149	0.960	0.197	0.000	1.000
	Acad	Variable counting the number of founders in the team heaving an academic title.	149	0.383	0.643	0.000	4.000

Table 5-1 continued

	Variable	Description	Obs	Mean	Std. Dev.	Min	Max
	OutsideConn	Binary variable, indicating whether the respective company has also connections to other networks than the one it is located in.	149	0.295	0.458	0.000	1.000
	Meanturb	Mean of industry turbulence in the time span of three years before the firm has been founded and the three years afterwards.	149	3.235	6.466	-0.394	23.241
Net_{-3}	$Innovators_{-3}$	Size of the innovator network the founders are connected to three years before the firm has been founded.	149	301.691	258.600	11.000	868.000
	$Aggregation_{-3}$	Level of aggregation of the network the founders are connected to three years before the firm founding.	149	0.054	0.055	0.013	0.273
	LC_{-3}	Size of the largest component of the network the founders are connected to three years before the firm founding.	149	0.117	0.076	0.045	0.364
Net_0	$Innovators_0$	Size of the innovator network the firm is connected to in the year of founding.	149	780.134	560.084	32.000	1836.000
	$Aggregation_0$	Level of aggregation of the network the firm is connected in the year firm founding.	149	0.055	0.066	0.011	0.246

Table 5-1 continued

	Variable	Description	Obs	Mean	Std. Dev.	Min	Max
	LC_0	Size of the largest component of the network the firm is connected to in the year of firm founding.	149	0.142	0.129	0.043	0.493
Net_{+5}	*$Innovators_{+5}$*	Size of the innovator network the firm is connected to five years after the firm has been founded.	149	1531.617	991.999	75.000	2875.000
	$Aggregation_{+5}$	Level of aggregation of the network the firm is connected to five years after the firm founding.	149	0.149	0.170	0.012	0.428
	LC_{+5}	Size of the largest component of the network the firm is connected to five years after the firm founding.	149	0.286	0.243	0.032	0.654

Table 5-2 Correlations of the variables used in order to assess the influence of the selective nature of the innovator network

		1	2	3	4	5	6	7	8	9	10	11
1	Net_{-3}	1										
2	$Net_{-3}SQ$	0.6745*	1									
3	Net_{0}	-0.3059*	0.0296	1								
4	$Net_{0}SQ$	-0.3157*	0.0016	0.8817*	1							
5	Net_{+5}	-0.4452*	-0.1395	0.7009*	0.4648*	1						
6	$Net_{+5}SQ$	-0.2098*	0.0133	0.5609*	0.5455*	0.7212*	1					
7	EV_{-3}	-0.3759*	-0.5851*	0.0283	0.0161	0.0537	-0.0208	1				
8	EV_{0}	-0.0854	0.0033	0.2395*	0.2649*	0.1329	0.1431	0.0076	1			
9	EV_{+5}	0.0475	0.0065	0.0586	-0.0095	0.0422	-0.0516	0.0111	0.0259	1		
10	MC_{-3}	0.2724*	0.4032*	-0.0509	-0.0218	-0.0858	0.0079	-0.8365*	-0.0068	-0.0005	1	
11	MC_{0}	0.0955	0.3298*	0.2229*	0.1793*	0.1522	0.2403*	-0.4250*	0.4013*	0.0098	0.4013*	1
12	MC_{+5}	-0.2021*	-0.0479	0.2680*	0.0815	0.4747*	0.2932*	0.0296	0.1709*	0.1678*	-0.0395	0.2510*
13	$Constr_{-3}$	-0.0084	0.0512	0.0536	0.0099	-0.0471	-0.0346	0.0751	0.0885	0.0057	0.0808	0.1661*
14	$Constr_{0}$	-0.0875	0.0227	0.1167	0.1329	0.0499	0.121	0.1641	-0.0381	-0.0021	-0.0173	0.0862
15	$Constr_{+5}$	0.0629	0.0023	-0.1083	-0.0477	-0.007	0.1129	0.1516	-0.1171	-0.0557	-0.0789	-0.0678
16	*#Patents*	-0.1708*	0.0554	0.0835	0.0061	0.078	-0.0457	-0.1137	0.2502*	0.0046	0.1007	0.1266
17	*PatExperience*	-0.1258	0.0225	-0.0487	-0.1093	0.0437	-0.1257	-0.0827	-0.0054	0.1034	0.0545	0.0281
18	*#Founders*	-0.1939*	-0.0675	0.0017	0.009	0.0191	-0.0797	-0.1158	0.1378	-0.0541	0.0367	0.0073

*p<=.05

Table 5-2 continued

		1	2	3	4	5	6	7	8	9	10	11
19	*Spinoff*	-0.3358*	-0.0649	0.3469*	0.3149*	0.3528*	0.2482*	0.022	0.1672*	0.0029	-0.0404	0.0718
20	*CapComp*	-0.0672	-0.1276	-0.1712*	-0.1779*	-0.0255	-0.0353	-0.0076	0.0168	0.0012	0.0168	0.042
21	*Acad*	-0.2506*	-0.0517	0.1121	0.0949	0.1685*	0.0292	0.0244	0.0792	0.0846	-0.0491	-0.069
22	*OutsideConn*	-0.0997	0.0155	-0.0789	-0.0506	-0.0083	-0.0661	-0.2532	0.127	0.12	0.127	0.1668*
23	*Meanturb*	-0.0588	-0.1453	-0.1335	-0.1072	-0.1148	-0.1339	0.2242	-0.0369	-0.0019	-0.0248	-0.089

*p<=.05

Table 5-2 continued

		12	13	14	15	16	17	18	19	20	21	22	23
12	MC_{+5}	1											
13	$Constr_{-3}$	0.1089	1										
14	$Constr_{0}$	0.0038	0.4045*	1									
15	$Constr_{+5}$	-0.0981	-0.001	0.3861*	1								
16	*#Patents*	0.2764*	0.3987*	0.2121*	-0.2157*	1							
17	*PatExperience*	0.1605	0.1245	0.0419	-0.2320*	0.4394*	1						
18	*#Founders*	0.0243	0.1345	0.0286	-0.1307	0.2655*	0.2095*	1					
19	*Spinoff*	0.1541	0.003	0.2514*	0.0695	0.0852	0.1079	0.1149	1				
20	*CapComp*	0.0985	0.0293	0.0413	0.0912	0.0754	0.0714	0.0767	0.0145	1			
21	*Acad*	0.0345	0.0589	0.0971	-0.0981	0.2544*	0.5281*	0.3177*	0.1827*	-0.0375	1		
22	*OutsideConn*	0.2159*	0.051	0.0274	-0.1107	0.2906*	0.4151*	0.1800*	0.2020*	0.1326	0.3712*	1	
23	*Meanturb*	-0.1551	0.0528	0.0174	0.1965*	-0.1285	-0.139	-0.03	-0.0603	0.0766	-0.1476	-0.1154	1

*p<=.05

Table 5-3 Correlation table for variables describing the network structure

	Variable	1	2	3	4	5	6	7	8	9
1	*$Innovators_{-3}$*	1								
2	*$Aggregation_{-3}$*	-0.5482*	1							
3	*LC_{-3}*	-0.4579*	0.9178*	1						
4	*$Innovators_{0}$*	0.9518*	-0.5870*	-0.4813*	1					
5	*$Aggregation_{0}$*	0.5725*	0.0463	0.1928*	0.4457*	1				
6	*LC_{0}*	0.5993*	-0.0202	0.1792*	0.4873*	0.9734*	1			
7	*$Innovators_{+5}$*	0.8106*	-0.5923*	-0.4853*	0.9477*	0.2551*	0.3049*	1		
8	*$Aggregation_{+5}$*	0.6004*	-0.2265*	-0.0093	0.7018*	0.5638*	0.6370*	0.6901*	1	
9	*LC_{+5}*	0.6208*	-0.2393*	0.0033	0.7103*	0.5554*	0.6568*	0.6873*	0.9805*	1

*p<=.05

5.6.1 Estimation framework

Since success is measured in terms of survival, we apply Cox's proportional hazards model (1972) which gives a valid estimate of the survival rate for data sets including right-censored and left truncated cases. In survival analysis typically the relationship of the survival distribution to several covariates is examined. In our model, the firms' hazard to die in the next period is dependent on covariates as the networks' structure, the founder's position in the network and the structure of his ego-network.

Since a (scientific) social network is not a static but a dynamic construct which is developing gradually (Gay and Dusset 2005), we have to take time dependent effects into account. The connectedness of the innovator network and also the founders' position in the net are changing over the organizational life cycle and it is also path dependent (Hite and Hesterly 2001). This would mean that the structure of the network and the position of the founder in this network is dependent on the past structure and position respectively. To cover the early three stages in the organizational life cycle, we decided to measure our dependent variables at three points in time: first three years before they found the firm ($t=-3$) is representing the nascent stage, exactly in the year of firm founding ($t=0$) is representing the beginning of the emergent stage and five years afterwards ($t=+5$) is representing the beginning of the early growth stage. This allows us to control for gradual effects with respect to the development of the networks' structure and to observe the coevolution of the network structure and the organizational life.

5.6.2 Variables

5.6.2.1 Measuring the structure of the regional innovator network

In order to measure the structure of the RIN, we use several graph-theoretic concepts. Regarding size, the straightforward way to measure is to count the number of nodes, which is the total number of inventors in the travel-to-work area (Lobo and Strumsky 2008). The variable $Innovators_t$ thus measures the total number of inventors based in a respective TTWA in the certain stage of the organizational life cycle.

We use two variables to capture the structural features of a regional innovator network. The first one is a concept we adopt from Lobo and Strumsky (2008) which is basically a Herfindahl index based on the distribution of component sizes. This variable *Aggregation*$_t$ measures the proportion of inventors in a RIN who are grouped into larger components[11] and variable ranges between zero and one, whereupon a value close to one indicates that most inventors in the TTWA are grouped into few components. In order to measure the extent to which inventors in a TTWA are intensely linked to one another we use as second variable the *size of the largest component (LC*$_t$*)*, which captures the share of inventors within the TTWA that had a collaborative relationship within the largest component.

Having a look at the correlation table for variables describing the regional network structure (Table 5-3), it is conspicuous that the three variables describing the structure of the network (*Innovators*$_t$*, Aggregation*$_t$ and *LC*$_t$*)* are highly and significantly correlated. Hence, we decided to apply factor analysis and to concentrate those variables to one factor "*Net*$_t$". Table 5-4 shows the results of this analysis for the three points in time nascent stage, emergence stage and early growth stage. The higher the value of this variable the larger, more cohesive and more connected is the network of the respective ttwa.

Table 5-4 Factor Analysis Network Structure

Variable	Net_t	Uniqueness
$Innovators_{-3}$	-0.7271	0.4713
$Aggregation_{-3}$	0.9573	0.0836
LC_{-3}	0.9278	0.1393
$Innovators_0$	0.6847	0.5312
$Aggregation_0$	0.9523	0.093
LC_0	0.9648	0.0691
$Innovators_{+5}$	0.8427	0.2898
$Aggregation_{+5}$	0.9675	0.0639
LC_{+5}	0.9666	0.0657

[11] For details see Lobo and Strumsky (2008), p.876.

In order to test hypotheses 5-1a-c and to find out more on the relationship between the structure of the regional innovator network and the success (survival probability) of the firm, we regress the variable Net_t together with different firm-specific control variables on the hazard ratio of the firm (this is the basic principle of the Cox regression model).
When we assess the relationship between the founders position in the net and the structure of the ego-net on the survival probability of the firm (Hypotheses 5-2a-c and 5-3a-c), we use Net_t as regional control variable. We have argued above that the characteristics and structure of innovator networks differs regionally. The networks, we have constructed for the analysis performed here, have been created for 12 ttwas in Thuringia such that the variable Net_t basically reflects the regional endowment with respect to the innovator network.

The variable Net_t measures the overall structure of the network the firm is connected to, irrespectively of the number of founders and the question of how many founders are connected to the network. In the next two steps of analysis, we distinguish between the position of the founder in the whole network and the structure of the ego-network. This is of cause estimated for single nodes. There is a small number of cases, where more than one founder is connected to the network. In these cases, we assumed a multiplicative effect and summed up the values for the nodes.

5.6.2.2 Measuring entrepreneur's position in the network

When analysing the founders' position in the network, we basically want to know how central he is in the network as such. In order to assess this, we use two concepts. First, centrality is measured here by means of eigenvector-centrality and reveals how well connected an actor is in the overall network (EV_t)[12]. The eigenvector approach identifies the most central actors in terms of the "global" or "overall" structure of the network (Hanneman and Riddle

[12] We measured centrality by means of Eigenvector centrality (Bonacich 1972). There exist different measures for centrality like betweeness centrality (Anthonisse 1971, Freeman 1977), closeness centrality (Beauchamp 1965) or hub centrality (Kleinberg 1999). We decided for the Eigenvector centrality since it is a feedback centrality which is showing whether the actor is connected to the top connected other actors in the net which might be especially useful for young and small companies who are in need of good contacts.

2005). Thus, by taking into account direct as well as indirect ties of single actors it assumes that a node is central to the extent that the node is connected to others who are central (Bonacich 1972). Higher scores indicate that actors are "more central" to the main pattern of distances among all of the actors, lower values indicate that actors are more peripheral. For the case that more than one founder is connected to the network, we summed up their individual values for EV_t.

The second concept we use is the membership in the main component. The main component of the network is the maximal connected sub graph. This measure thus captures the degree of fragmentation in a RIN's structure. If the network has more than one component, different information flows pass each component. Since the main component connects the largest number of nodes, being connected to this component may induce most knowledge flows (Powell et al. 1996). With respect to the RIN, this means that a networked-founder which is a member of the main component is more central to the network and thus his firm profits comparably more from network's knowledge flows. MC_t takes a value of one if (one of) the entrepreneur(s) of the firm is connected to the main component and is zero otherwise.

5.6.2.3 Measuring the ego-network of the entrepreneur

In order to assess the influence of the closeness of the networked-founder's ego-network, we use the variable $Constr_t$ which is a structural hole measure introduced by Burt (1992). This is a summary measure that taps the extent to which ego's connections are to others who are connected to one another (Hanneman and Riddle 2005). A high value of this variable indicates that the entrepreneur occupies a position in the net which is less constrained and where he can broker more extensively. In other words, the higher this measure, the less structural holes the ego-network has and the more closed it is. For the case that more than one founder is connected to the network, we summed up their individual values for $Constr_t$.

5.6.2.4 Control Variables

In order to compare and contrast the effects of network structure as well as founders' position in the net and firms' characteristics on survival we, additionally to the dependent variables introduced in the above chapter, used a set of control variables which may influence firms' survival.

#Patents. This variable counts the number of patents the founders of the firm applied for after the firm has been founded. Founders with more patents might be more connected to the network such that in order to make statements on the main variables of interest in this paper, we need to control for the quantity of patent applications.

PatExperience. This is a variable counting the number of patents the founders of the respective firms have applied for before the firm has been founded. Cantner and Wolf (2016) found that experience in patenting is a main driver of patenting in the future such that this influences the founders future network which we want to analyze.

#Founders. This variable indicates the number of persons that has founded the respective firm. It has been argued earlier in this text that more founders may bring a broader range of scientific capital to the firm and thus also influence firms' success.

Spinoff. This dummy variable measures whether the firm is an academic spin-off or not. Academic spin-offs are usually founded on the basis of innovative products and additionally have the 'mothers' support, which makes them more successful (Utterback 1974).

CapComp. This variable indicates weather a firm has the legal form of a capital company (*Capcomp*=1) or of a private company (*Capcomp*=0). It has been found that private companies may have higher chances to be successful, thus to survive, since the founders adhere with their private capital (Harhoff et al. 1998).

Acad. This variable counts the number of founders with an academic title. It has been found that academics usually have a larger network of scientific contacts (Breschi and Catalani 2010) and may therefore add more to the scientific network of the firm.

OutsideConn. Being connected to more than on RIN may enlarge the scientific network of the firm. Thus, with this variable, we measure whether the firm has connections to more than the RIN where it is located at.

Meanturb. The firms in the sample are active in different industrial sectors and of cause the sector plays an important role to for the survivability of a firm. Since this paper is analyzing young firms, it is not only controlled for sectors but to also for the economic environment/stage of the sector they are active in. For this purpose, data from the IAB (Institut für Arbeitsmarkt- und Berufsforschung) has been used, which contains the number of firm founding and closing for each industry (Nace 2-digit level) for the years 1976 to 2010. Based on this data, the variable named *Meanturb* has been constructed, which is measuring the turbulence in the sector the firm is active in for a time span of six years, three years before the firm has been founded and three years afterwards. The turbulence is measured as number of firm founding in a certain sector in the specific years minus the number of firm close downs in the same sector in the same years. From this value, the mean over the six years around the firm founding is estimated and used for analysis.

5.7 Empirical results

Hypothesis 5-1a states that there is no connection between the structure of the network and the chances for a firm to survive in the nascent stage of the organizational life cycle, while hypothesis 5-1b and 5-1c suggest a decreasing importance of the connectedness of the network and firm survival. In order to measure how dense the whole network is, we applied factor analysis and created the variable Net_t which is the combination of three variables describing the network as such (size of the network, aggregation level of the network and size of the largest component). The larger the variable Net_t the more connected the network in the sense that there are more actors which are highly aggregated and which's largest component is relatively big. Table 5-5, model 1 provides the results for all three stages in the early organizational life cycle. We do not find a significant relationship between the survival of the firm and the network structure in the nascent stage and year of firm founding/beginning of the emergent stage and thus have to accept hypothesis 5-1a and to reject hypothesis 5-1b. However, we find a significant relationship between the hazard ratio and the network structure five years after firm founding (Net_{+5}), when the early growth stage develops. The coefficient of Net_{+5} is larger than one, which means that the risk to die in the next period is increased when the connectedness of the network is increased. This supports hypothesis 5-1c. The squared term of Net_{+5} ($Net_{+5}SQ$) however is smaller than one which indicates that from a certain network size on, the hazard starts to become smaller again. This inverted u-shape relationship between network size and the survival of the firm indicates that there are two favorable situations for the firms. Either they are connected to a network which is quite fragmented or to a network which is extremely connected. This finding might be due to the fact that Hite and Hesterly (2001) are right in their assumption that the cohesiveness of the network decreases while the bridging of structural holes increases over time. Since we could not observe the exact date of movement between the two stages in the organizational life cycle but only narrowed this date by assuming that this might happen after roughly five years (Phillips and Kirchhoff 1989) it might just be that after five years some firms are still in the emergence firms (cohesiveness is important) and others already went to the early growth stage (structural holes are important).

Hypotheses 5-2a-c relate to the overall centrality of the position of the founder in the network. While hypothesis 5-2a suggests no relationship between the survival in the nascent stage and a central position of the founder, hypothesis 5-2b and 5-2c suggest a positive influence of a central position on the chances to survive, but for different reasons. In order to measure this relationship, we use Eigenvector centrality, as well as the membership in the main component.
Model 2 in Table 5-5 analyzes the variables EV_{-3}, EV_0 and EV_{+5} as representatives of the actors Eigenvector centrality. We find that only the coefficient for EV_{-3} becomes significant, a result that interestingly stands against our hypothesis 5-2a stating no connection between survival and centrality in the nascent

stage. Rather a central position seems to hinder survival. Looking at the membership in the main component, we find a significant result for the early growth stage. However, in contrast to hypothesis 5-2c, we find a negative relation. If we reinterpret this result in the light of Hite and Herstely's (2001) proposition that in the later stages, firms do not need a very dense network anymore, we might say that also the connection to the main component becomes unfavourable at a certain point in the life cycle. Therefore, the power argument of being in a position to control knowledge might not be that strong for our database.
Finally, although we find significant relationships, we have to reject hypotheses 5-2a-c.

Hypothesis 5-3a states that closed ego networks of a networked-founder in the nascent stage have no influence on its survival. In model 4 of table 5-5, we use the variable $Constr_{-3}$ to measure this relationship and find no significant relationship such that we cannot accept hypothesis 5-3a. Hypothesis 5-3b and 5-3c, taken together, state that from the emergent to the early growth stage in the organizational life cycle, the favourable network moves from a closed one to a quite fragmented one. In table 5-5 we find no significant effects.

Over all models in table 5-5, the variable measuring the connectivity of the whole network shows up to be significant at the beginning of the early growth stage. But this relation takes an inverted u-relationship.

Table 5-5 Influence of the network structure and the ego-network on the hazard ratio

	Cox regression – Breslow Method for ties							
Dep. Var.	survival							
	model 1		model 2		model 3		model 4	
	H1a-c		H2 a-c		H2 a-c		H3 a-c	
EV_{-3}			1.034	*				
			(1.721)					
EV_{0}			0.000					
			(-0.000)					
EV_{+5}			1.010					
			(0.168)					
MC_{-3}					6.010			
					(0.000)			
MC_{0}					0.000			
					(-0.000)			
MC_{+5}					4.567	***		
					(2.811)			
$Constr_{-3}$							0.791	
							(-0.428)	
$Constr_{0}$							1.332	
							(0.573)	
$Constr_{+5}$							2.124	
							(1.376)	
Net_{-3}	1.214		1.192		0.938		1.172	
	(0.640)		(0.579)		(-0.211)		(0.523)	
$Net_{-3}SQ$	0.928		0.947		0.990		0.921	
	(-0.521)		(-0.379)		(-0.068)		(-0.550)	
Net_{0}	0.715		0.701		0.731		0.810	
	(-0.577)		(-0.599)		(-0.551)		(-0.348)	
Net_{0} SQ	1.134		1.142		1.158		1.091	
	(0.523)		(0.542)		(0.607)		(0.350)	
$Netplus_{+5}$	2.355	**	2.512	**	1.539		2.426	**
	(1.982)		(2.086)		(0.974)		(2.011)	
$Netplus_{+5}$ SQ	0.509	*	0.484	*	0.575		0.444	**
	(-1.842)		(-1.940)		(-1.535)		(-2.140)	

Robust z-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.10

Table 5-5 continued

Method Dep. Var.	Cox regression – Breslow Method for ties survival							
	model 1 H1a-c		model 2 H2 a-c		model 3 H2 a-c		model 4 H3 a-c	
Patthvor2	0.918		0.915		0.879		0.918	
	(-0.794)		(-0.819)		(-1.165)		(-0.714)	
Patth2	0.950		0.950		0.968		0.963	
	(-0.941)		(-0.934)		(-0.561)		(-0.660)	
Grnder	1.442	**	1.473	**	1.408	*	1.532	**
	(1.985)		(2.100)		(1.917)		(2.223)	
Spinoff	0.170	**	0.172	**	0.169	**	0.122	**
	(-2.291)		(-2.283)		(-2.234)		(-2.565)	
Capcomp	0.435		0.421		0.386		0.339	
	(-1.234)		(-1.281)		(-1.390)		(-1.538)	
Acad	1.501		1.464		1.612		1.391	
	(1.249)		(1.168)		(1.375)		(0.994)	
Outsideconnection	0.558		0.569		0.360*	*	0.605	
	(-1.158)		(-1.098)		(-1.825)		(-0.995)	
Meanturb	1.022		1.016		1.025		1.012	
	(0.916)		(0.644)		(1.031)		(0.455)	
Observations	149		149		149		149	
No. Of Failures	38		38		38		38	
Prob>Chi2	0.0185		0.0318		0.0042		0.0230	

Robust z-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.10

5.8 Conclusions

Over all analyses, we find that there is no influence of the networks' structure in the nascent stage of the organizational life cycle. This supports the findings by Cantner and Stuetzer (2013) who show that factors like start-up capital, the functional background and entrepreneurial experience of the founders seem to overweight the importance of social (scientific) capital for the success of the new venture. However, for Eigenvector centrality, we find a small negative effect indicating that a central position in the innovator network is not too favourable in the nascent stage of the firm' life. A reason might be the high inflow and redundancy of information, reaching a node in a central position. A person which has to concentrate on getting start-up capital and writing a business plan might easily be overstrained by this. For sure, this point leaves open space for further research.

Having a look at the structure of the 'home' network of the firm, we find an inverted u-shaped relationship between the survival of firms and the connectivity of the network. Thus, very loose networks and very dense networks seem to be favorable for the survival of firms but nothing in between. Additionally, we find that it becomes unfavorable to be connected to the main component when the firm enters the early growth stage. In the theoretical part of this paper, we argued that Burt (1992) and Coleman (1988) have two opposite views on the interdependency between the structure of the ego-network and the related benefits for the actor (Gilsing et al. 2008, Gilsing and Nooteboom 2005). While Burt says that a loose network is favorable since it brings possibilities to broker and control knowledge flows, Coleman says that dense networks are favorable since they allow for more knowledge spillovers. Hite and Hesterly (2001) translate these considerations to the organizational life cycle and argue that firms need a "Coleman-network" in the emergent stage but a "Burt-network" when they enter the early growth stage. The inverted u-shape we find might be due to the individuality of each firm's history. Some firms might change to the early growth stage already after two years, while others need six. What the results show is that Burt and Coleman both have their eligibility. Additionally, Hite and Hesterly seem to be on the right track with their idea of changing requirements on the network over the organizational life cycle. In a future research, it would be recommendable to have survey data and identify the moment when a firm leaves one stage and enters the other individually.

With respect to the influence of the founder's position in the network on firms' success, we looked at his centrality and on his membership to the main component. We find that being a member of the network's main component has a negative influence on the survivability of firms in the early growth stage. Thus, we disproved our theoretical argumentation, stating that the main component inherits most knowledge spillovers and thus increases the number of opportunities for innovation. However, also here, the arguments raised above may hold. In the largest component, the actors may all work in the same technology such that there is less variety of technologies which may be unfavorable for new combinations and thus firms' performance, especially in the later stage of the early firm development.

With respect to control variables we find that firms have better chances to survive if they are a spin-off and if they have connections also to other networks than only to the one in the region where they have their headquarters. This positive effect of a mother institution for highly innovative firms has already been described and empirically analyzed by Cantner and Goethner (2011). However, the influence of various connections to different networks seems to be an interesting issue. Is it important to which ones of the regional networks the firms are connected to? Is it possible for firms to be overconnected? Is there an optimal rate of outside connection? These and other questions are still open for future research.

Having a look at the mere number of founders, we find a negative effect on survival. Thus too many founders reduce a firm's chances to survive. In the theoretical part of this paper, we argued that the number of founders may have a positive influence since they may all add to the scientific network of the firm. However, Cantner, Goethner and Stuetzer (2010) found that the composition of the team plays an important role for the success of a firm. Their findings may explain our results since they showed that it is not quantity but quality of the founding team that counts and our results also go into this direction.

Additionally, Lobo and Strumsky (2008) argued that the variable network aggregation also indicates whether actors in the region have worked in the same technology. Interpreting our results from that angle our results point to the interpretation that variety of technologies in a network is favorable for firms' success. Since this interpretation is very vague it leaves space for future research.

6. Innovative start-up patenting: a new approach towards identification and determinants

6.1 Introduction

Patents have been and are still frequently used in innovation studies (Brouwer and Kleinknecht 1999). Network studies also comprehensively use and have used patents as an indicator for cooperative R&D activities (for example Breschi and Lissoni (2006) analysed inventor networks, Cantner and Graf (2006) analysed applicant networks). Scherer (1983) was the first to attempt to systematically investigate firms' propensity to patent. In his argumentation, one reason why patenting is important to firms is that they contribute to monopoly power and first mover advantages. In this way, patents are drivers of the Schumpeterian (1912) idea of creative destruction and innovative competition as drivers for economic development.

This paper is devoted to this old research question, to which no satisfactory answer has yet been found, and it also asks about young and innovative firms: ***What are the determinants of innovative start-ups' propensity to patent?***

The interesting fact, which is to be analysed in this paper, is that not every firm has the same propensity to patent. This means that, given a certain amount of innovation intensity, different firms may differ with respect to patenting intensity (Griliches 1990, Brouwer and Kleinknecht 1999). The causes for differences in patenting intensity are manifold. Scherer (1983) analysed the relationship between 1974 R&D expenditures and invention patenting by 4,274 lines of business in 433 US industrial corporations and found that the propensity to patent strongly varies across sectors but also modestly across firm characteristics such as overseas sales, federal R&D support, diversification, scope of invention use and invention type.

A year later, Bound et al. (1984) asked the questions: who does R&D and who patents? In order to find an answer, they investigated information on sales, employment, book value, pre-tax income, market value, R&D expenditures and patents applied for in 1976 for 2,595 firms in the manufacturing sector. Of these firms, 1,492 reported that they conducted R&D in 1976. With respect to the first question, they found that the industry determines who conducts R&D. Turning to the second question, they found that some of the firms which do

R&D also patent, and that there is a strong positive relationship between the two activities. Additionally, those small firms that do R&D tend to patent more per R&D dollar than larger firms.

However, Brouwer and Kleinknecht (1999) criticised these early attempts by Scherer (1983) or Bound et al. (1984) by saying that such comparisons have the weakness that they cannot distinguish between a less efficient use of R&D inputs and (real) differences in the propensity to patent. In their paper, they solve this problem by measuring the results of the innovation process such that they analyse whether firms with a given innovation output, measured as the propensity to file at least one patent, differ with respect to their patenting intensity.

Moreover, Kleinknecht (1987) compares the results of the official Dutch R&D survey with findings of his own innovation survey in the Dutch manufacturing industry and concludes that there is an undercounting of small business R&D which is often informal and on a smaller scale compared with large firms (see also Pavitt and Patel (1988) making the same observation). Additionally, Blind et al. (2006) find that larger firms are more often inclined towards patenting activity for strategic reasons. This undercounting implies that the propensity to patent will be systematically biased by firm size if it is analysed in the way Scherer and Bound et al. did (Brouwer and Kleinknecht 1999). Moreover, (at least applicant-) networks that are created on the basis of patent data are biased towards larger firms (ter Wal and Boschma 2009).

Besides the undercounting of small firm R&D, these findings additionally suggest that different laws may govern the groups of small firms and larger firms (Bound et al. (1984) already implicitly mention this point). Hall et al. (2012) even argue that start-ups constitute their own group among the group of small firms. Although there is now a broad literature investigating small and innovative firms in many respects (for example Acs and Audretsch 1990), there have been fewer attempts to analyse the factors related to the propensity to patent of these firms, not to mention for the group of innovative start-ups.

This paper is trying to fill this gap in analysing the propensity to patent of young and innovative firms in the eastern German federal state Thuringia. A data set is used which comprises information on R&D, capital stock, state promotion etc for 534 firms in their first three business years. Besides having the benefit that firm-level data (derived from a questionnaire) is combined with patent data (from the German Patent Office), the analysis has two advantages. First, it takes care of the problem that simply relating R&D to patent data leads to a mixing of a more or less efficient use of R&D and the propensity to patent (Brouwer and Kleinknecht 1999). Second, former studies basically matched patent data and survey data by searching for company names on the applicant side of the patent dataset. However, founders of young firms may show a tendency to apply for patents in their own names in order to avoid the risk of losing the property right after the firm has failed. Thus, the approach which has been used in former studies may lead to an undercounting of small and young firm patenting, simply because the wrong identification approach has been applied. A descriptive view on the data at hand reveals that only roughly 5.5% of the small and young firms apply for patents in the name of the company, the rest applies on the name of the founder(s). According to this, one may argue that not taking founders as applicants into account leads to an underestimation of small and young firm patenting as in the study of Hall et al. (2013). This paper is trying to avoid such undercounting by using a new approach towards the identification of firms' patents. Instead of only searching the patent data base for the names of the firms, also the names of the founders have been searched such that the tendency in young and innovative firms to apply for patents in the founders name has been taken into account.

6.2 Determinants of start-ups' propensity to patent

There is already a great deal of literature dealing with the decision to patent or, in other words, with the propensity to patent of firms. Hall et al. (2012) give a broad literature overview on the choice between formal and informal securing of intellectual property rights. They describe the decision to patent or not as a trade-off between the benefits from using informal intellectual property rights and the costs that arise from it compared to relying on informal methods such as secrecy. As regards costs, financial expenditure and the possibility of enforcing the property right have to be taken into account. The benefits of safeguarding property rights arise basically from the ability to exclude competitors from the use of a new technology and from the potential to receive royalty fees if the patent is licensed (Arundel 2001, Harter 1994). Additionally however, patenting has advantages such as signalling the quality of an invention, improving public image, increasing bargaining power and the possibility of signalling expertise to potential research collaborators (see Hall et al. 2012).

However, one main finding of the well-known Yale and Carnegie-Mellon surveys is that patenting strategies vary greatly across firms of different size. Although large firms generally use the patent system at a lower cost per patent than smaller firms, Hall et al. (2012) argue that those firms specialising in knowledge production and the proof of innovative concepts may be small and that patenting becomes important for them since their assets are based on knowledge. However, even among small firms, start-ups may be a group of their own and have strategies that are different from those of established small firms (Hall et al. 2012).

Regarding the patenting behaviour of young and innovative enterprises, two time dimensions have to be taken into account. First, there is the pre-founding phase, where the founders may work on their business idea and already apply for a patent that is then commercialised by means of creating the business (Walter et al. 2010). Since the founder's behaviour may be path-dependent, patenting activities in advance of founding the business may influence patenting over the whole lifespan of the firm. Additionally, it may be the case that a firm based on an invention which is so important that it has been patented may be innovative enough to go on patenting during its business years.

Second, after the firm has started, its characteristics influence whether it applies for patents or not. Analysing the 2008 Berkley Patent Survey, Graham et al. (2010) as well as Graham and Sichelman (2010) find that there are important differences in the patenting behaviour regarding the industries the firms are working in. Also they find that strategic motives play a large role in start-ups' decision to patent. Start-ups seem to value the reputation effect that comes with very high rates of patent ownership. However, Graham et al. (2010) also find that financial constraints are most frequently the highest barrier to patenting for young firms. Analysing 370 US start-ups in the semiconductor industry, Hsu and Ziedonis (2008) find that patents can act as a signal for start-ups' innovativeness such that patenting firms may progress through the venture capital rounds of financing institutions more successfully. Additionally, Cantner and Kösters (2009) find state promotion to have a positive influence on start-ups' propensity to patent. Of course, such variables as the R&D intensity, cooperation, competition and the characteristics of the innovation (which also important for non-start-ups) may also play a role (Hall et al. 2012).

6.2.1 Pre-founding phase

Before starting-up the firm, the potential founder, known as a nascent entrepreneur, is actively engaged in creating a new venture of his own (Wagner 2004). Among other activities, nascent entrepreneurs think seriously about their business, look for facilities/equipment, initiate savings to invest, invest money in the firm, organise the start-up team, write a business plan, buy facilities/equipment, search for financial support and licence/patent (see Wagner 2004; Reynolds 1997; Reynolds and White 1997). Walter et al. (2010) analysed the patenting behaviour of scientists before and after creating a spin-off and find that scientists increasingly commercialise their inventions through firm formation. However, potential founders who are not working as scientists may also conduct research and apply for a patent before and after creating a start-up. Walter et al. (2010) argue that the nascent entrepreneur (and this also holds for the entrepreneur in the business years of the firm) faces a trade-off between the patenting or otherwise protection of his business idea. On the one hand, patenting safeguards the knowledge base of the new venture against early imitation but on the other hand it facilitates early imitation by disclosing exactly this knowledge base (Arundel 2001, Harter 1994). Walter et al. (2010) find for academic founders that academics are more likely to patent if the search for marketable applications of the invention is highly uncertain, the technological field is rapidly changing, the field of research is one with high patent protection and the spin-off has high entrepreneurial orientation in the sense that the founders of the firm are innovative, pro-active and take risks. Thus, there are some factors influencing the nascent entrepreneurs' propensity to patent. But to what extent does this early patenting and R&D activity influence innovative success and thus patenting after the business has been launched? Firms that are built upon an innovation (be it patented or not) may have a higher propensity to innovate successfully in the future and thus patent more during their business life. This goes back to Dosi et al.'s (1997) stylised facts of industrial dynamics that hold that there is significant heterogeneity in firm characteristics, behaviour and performance and that such diversity appears to be persistent. This means that prolific innovators at time *t* have a higher probability of remaining prolific innovators in period *t+1*. Although Giovanni Dosi did not relate his work on stylised facts to entrepreneurial activities, they may hold also for this field of research. Crépon and Duguet (1997) indeed find that past success in the production of innovation increases R&D efficiency. However, this effect seems to be non-linear in the sense that a small but positive number of innovations in the past positively affects the production of innovations in the present but this effect vanishes if the number of innovations increases.

Taking into account the arguments made above, one may formulate hypothesis 6-1 in the following way:

Hypothesis 6-1:
Patenting behaviour is path-dependent in the sense that patenting in the preparation process for founding the firm increases the patenting intensity after the firm has been founded.

6.2.2 Business years

In its business years, a start-up may be characterised by certain factors that influence the propensity to patent.

a. State promotion

Cantner and Kösters (2009) find that R&D-subsidised start-ups show a 2.8 times higher patent output and argue that these estimates provide evidence for the additionality of R&D subsidies within the first three business years. They reason as follows: state promotion may have an influence on patenting propensity for two reasons. Innovative firms receiving such programmes may have more financial scope, which may make it easier to apply for a patent and those firms may be more innovative since they have to apply for this support in a process where referees evaluate the innovativeness of their business idea. Following these arguments, an overall positive influence of state promotion on the propensity to patent may be expected. Hypothesis 6-2 thus states:

Hypothesis 6-2:
Start-ups receiving state promotion show a higher patenting intensity.

b. Venture Capital

Applying for a patent and managing the patent portfolio is expensive. For small high-tech firms, Cordes et al. (1999) find that the costs of applying for and enforcing a patent were the leading reason why firms do not generally use patents. For start-ups, Graham et al. (2010) as well as Graham and Sichelman (2010) found that financial constraints are the most significant barrier to patenting.

Firms starting with more money may find it easier to patent their business idea whereas 'poorer' founders may abandon this device of securing their idea and use the remaining money for other purposes. Additionally venture capital is usually given to young and innovative firms with high growth potential. Thus, if a firm receives venture capital, it does not just have more money to work with. Receiving venture capital also signals that this firm is seen (at least by the investors) as highly innovative with excellent future prospects.

According to these arguments, Hypothesis 6-3 will be:

Hypothesis 6-3:
Start-ups with a venture capital budget are more innovative, can more easily apply for patents and will therefore patent more.

c. Cooperation

With respect to cooperative R&D activities, Brouwer and Kleinknecht (1999) argue that patenting serves as a vehicle for the formalisation of technology exchange agreements. They expect firms engaged in R&D collaboration projects to have an above-average propensity to patent since patenting may make it easier to treat a firm's knowledge as a tradable asset when it comes to negotiations over the conditions of technological partnerships. Additionally, Cowan et al. (2006) showed that cooperation has a positive effect on innovativeness and thus on patenting.

Based on these arguments, Hypothesis 6-4 may be formulated as follows:

Hypothesis 6-4:
Firms that cooperate patent more since they are more innovative.

d. Scientific orientation

In general, patenting is associated with the R&D activity within firms (Hall et al. 2012). If a firm's R&D is basically devoted to the newest scientific insights, the results of these activities may be new enough to be patentable. Thus, for firms conducting science-oriented R&D, the propensity to patent and their patenting intensity may be higher. As a consequence one may formulate Hypothesis 6-5 as follows:

Hypothesis 6-5:
Firms conducting science-oriented R&D are more active in patenting with regard to the number of patents applied for.

6.3 Database and variables

Most of the recent empirical analyses on the impact of firm and industry characteristics on the propensity to patent use data from the Community Innovation Survey (CIS), which has the advantage that it contains information on product and process innovation and on different channels for appropriability methods. Additionally, it provides cross-country insights that have already shown that some empirical regularities exist with respect to firms' propensity to patent. However, the database may underrepresent young and innovative start-ups since firms have to have at least 10 employees to be considered for the questionnaire. The questionnaire used as the basis for the data analyzed in this research paper has been specifically addressed to young and innovative firms, asking questions about the time period between three years before and after the firm was founded. Looking at the number of employees the firms had in the third business year, it becomes obvious that 72.68% have fewer than 10 and would not have been considered for the CIS.
Additionally, it is a new and doubtless useful trend to combine the CIS data with patent databases (e.g. Hall et al. 2012, Heger and Zaby 2012). This is usually done by matching the names of firms in the CIS with the names of applicants. However, using these combinations of databases, it is often found that small firms are less likely to patent than bigger firms. This paper will not argue against this finding but proposes a new approach for identifying firms' patents which may fit better for small firms and especially for young and innovative

ones. Usually, when a firm is bankrupt, intellectual property rights are part of the remaining assets of the insolvent corporation. For newly-founded firms, the hazard of failing may be high enough for it to make sense to apply for a patent in the founder's name rather than in the firm's name since the founder can maintain ownership of the intellectual property even after the firm has collapsed. Therefore, when identifying firms' patents, patents applied for by the founders also have to be taken into account. A short descriptive analysis of the data at hand supports this idea. Among 534 firms in the database, 64 (11.89%) had patents in the first five business years. However, only 5.46% of the patents the 64 patenting firms applied for have been filed under the name of the firm. The rest were applied for under the name of the founder(s).

6.3.1 Database

The data used in the analysis was provided by the Thuringian Founder Study (Thüringer Gründer Studie), an interdisciplinary research project on the success and failure of innovative start-ups in the eastern German federal state of Thuringia. This dataset draws from the German trade register (Handelsregister, Abteilung A/B) for commercial and private companies established in Thuringia between the years 1994 and 2006. It is further restricted to start-ups in innovative industries, comprising 'advanced technology' and 'technology-oriented services' according to ZEW classification (Grupp et al., 2000). Furthermore, in addition to economic information, it contains information on the socio-demographic profile and psychological characteristics of the founders.

The survey population consists of 4,215 founders who registered 2,971 new entries in the Handelsregister. From the survey population, a random subsample of 3,671 founders was drawn and contacted. Due to team-started ventures, this corresponds to 2,604 start-ups in innovative industries. From January to October 2008, 639 structured face-to-face interviews were conducted with either the solo entrepreneur or with the lead entrepreneur of team start-ups. This resulted in a response rate of about 25%. There is no response bias with regard to industry structure and gender of founders.

The structured interviews were carried out by the members of the research project who were also supported by trained student research assistants. On average, an interview took approximately one-and-a-half hours. Retrospective data were collected relating to events in the founder's life and history of the business, covering the venture creation process and the first three business years of the start-up. To overcome entrepreneurs' hindsight bias and memory decay (Davidsson 2006), the survey used memory aid techniques drawn from the Life History Calendar method (Caspi et al. 1996). The focus on firms in a single region (the German federal state of Thuringia) further allows holding constant key labour market and environmental conditions. Another important advantage of the study design is the possibility of interviewing founders of companies that had failed at the time of data collection. Hence, the sample is not biased toward surviving or successful firms.

Due to the fact that some of these start-ups were not genuinely new but subsidiaries or diversifications of existing companies and due to incomplete data some observations had to be excluded from the analysis. This reduced the number of valid interviews to 534.

Patent information was drawn from the German Patent Office. For the 534 firms where a face-to-face interview with either the solo entrepreneur or with the lead entrepreneur of team start-ups was conducted, the patent data base was searched for inventors with the same name as each of the founders. If a match was found, the members of the research project contacted the founders personally to ask whether they really applied for these patents. Furthermore, patents were searched for that were applied for directly by the start-ups in the sample. This procedure captures potential patents for innovations developed by employees working for the start-ups. The sum of patent applications was calculated for the three years before the first business year as well as for the first three business years. Double counts resulting from co-patenting of the founders were eliminated. Out of 534 firms where information on patent activity could be found, 64 (11.98%) applied for patents during the first three business years. The number of patents ranges between one and 16 patents per firm within the first three business years. As an example to stress the worthiness of the new approach by considering the following: The 64 firms who applied for patents applied for 663 patents in sum. Among these 633 patents, only 38, this makes 5.46% have been applied for in the name of the company, the rest goes to the name(s) of the founder(s). This means that by using the other approach – which is identifying the patents only by searching the company name in the patent

data base – only 5.46% of the patents that are related to the firms would have been identified.
Summary statistics for the variables used can be found in table 6-1.

6.3.2 Dependent variable and method

The outcome variable of interest for the analysis conducted in this paper is *No.Patents,* which represents the number of patents applied for by a firm during its first three business years. Although the number of patents applied for has been researched for all of the firms, it does not mean that each firm has also conducted R&D and tried to find a patentable invention. Thus the two reasons for reporting a zero count with regards to the number of patents applied for may be that the firm was unsuccessful in its innovation strategy or that the firm has simply not tried to be innovative. If the firm didn't try to innovate, the outcome would always be zero. However if the firm tried to innovate, the outcome could be zero or positive. Thus, two processes are going on that can produce zeros: unlucky R&D or no R&D at all (Falk 2014).
Looking at the database with regard to R&D activities in the first three business years, one can see that 324 firms are active and 19.75% (64) of them also applied for patents. This means that among the observations with a zero count in the number of patents, 210 have it because they did not conduct R&D at all and 260 count the zero because of unlucky R&D. Of course one has to be aware that unlucky R&D can also mean that the firm did not have enough money to apply for a patent, didn't count property rights as the right way to protect its knowledge or is waiting to apply for a patent for strategic reasons.
The most commonly used regression model for count data, which is the Poisson regression model, cannot be applied for the data at hand for two reasons. Apart from the fact that the variable *No.Patents* contains excessive zeros, it is also not surprisingly the case that 59.57% applied for one or two patents, the rest applied for between three and 16 patents. Thus the observations are skewed to the left. Additionally, the variance of the outcome variable (1.48) is quite large as compared to the mean (0.35), which might be an additional indication of over-dispersion (Cameron and Trivedi 2013).
This leads to the conclusion that the Poisson regression model doesn't fit the data and it appears that the variance of *No.Patents* is increasing faster than the

Poisson model allows. In order to correct for overdispersion in the variable, negative binomial models have to be used for the analysis (Hausman et al., 1984). Since, as described above, the excess zeros are generated by a process separate from that generating the count values, zero inflated negative binomial regression models are used. The zero inflated negative binomial model is a combination of two distributions, where the zeros stemming from not conducting R&D are assigned to the probability p and the rest *(1-p)* to a negative binomial distribution (Mwalili et al. 2007). From a formal point of view, the zero inflated negative binomial distribution is given by (see Mwalili et al. 2007):

$$P(Y=y)\begin{cases} p+(1-p)(1+\frac{\lambda}{\tau})^{-\tau}, y=0 \\ (1-p)\frac{\Gamma(y+\tau)}{y!\Gamma(\tau)}(1+\frac{\lambda}{\tau})^{-\tau}(1+\frac{\lambda}{\tau})^{-y}, y=1,2,... \end{cases}$$

where the Y's represent the patent counts for a single firm; $\frac{1}{\tau}$ can be interpreted as an overdispersion parameter such that when it becomes close to zero, the zero inflated poisson model should be used; p represents the probability of excess zeros. The probability of excess zeros in the patent count is then estimated as a logistic regression with $\log(\pi) = Z_i\beta$.

The resulting coefficients can be interpreted as the expected change in the log of the number of patents applied for if the explanatory variable is increased by one unit (holding the other variables constant).

6.3.3 Inflation

As already described above, the excess zeros in the count outcome variable *No.Patents* can result from unsuccessful R&D or no R&D at all. Since R&D activities usually take some time until a patentable innovation can be obtained, the inflation has to be analysed using the variable *R&DpreFounding* which is a binary variable indicating whether there have already been R&D activities in the three years before the firm has been founded. This variable has been derived from the question: *With respect to your product or service: did you con-*

duct R&D in the three years before you started your business? Having a descriptive look at the data at hand, one finds that 42.1% of all firms (532) had already conducted R&D in the three years before the firm was founded. Of these, 21% (47) applied for patents in the first three years after the firm was founded.

6.3.4 Negative Binomial Regression

a. Pre-founding patenting

Hypothesis 6-1 states that the patenting behaviour of a firm during its business years is dependent on past behaviour. The variable *PatentsBefore* measures whether one of the founders applied for a patent in the three years before founding the firm. Looking at the data, one sees that about half of the firms that applied for patents in the three years before the firm has been founded also applied for patents in the three years afterwards.

b. R&D promotion

The variable *R&DPromotion* was derived from the question: *Did your firm draw on promotion for research and development in the first three business years?* This variable is one if the firm received state support and zero if not. In order to make it easier to remember this detail for the founder being interviewed, a list of German and Thuringian R&D promotion programmes was provided. As argued above, promotion for R&D may positively influence the patent output in terms of the number of patents a firm applies for.
Descriptive statistics reveal that among 353 firms where there is an observation, only 35.7% (126) received R&D support. 27.0% (34) of them applied for a patent in the first three business years.

c. Venture capital

The binary variable *VC* measures whether the firm received venture capital at the beginning of the first business year and is derived from the question: *Was there private venture capital available to your firm at the beginning of the first business year?* This variable is one if the answer is yes and zero otherwise. Venture capital, also called risk capital, is a temporary financial interest in young, innovative and non-market listed companies that are characterised by

an above average growth potential. Thus, a firm receiving venture capital is evaluated by external persons to be more innovative than other firms and by receiving the money, this firm may find it easier to patent.
In the database at hand, receiving venture capital is quite a rare event. Only 21 of 364 firms (there have been many omissions in the database) received venture capital, which is a share of 5.7%. Four of them (19.0%) applied for a patent within the first three business years.

c. Cooperation

The variable *cooperation* is a binary variable and indicates whether the firm had cooperation projects in R&D or not. It is derived from the question: *Within the first three business years, did you cooperate in R&D?* The variable is one if the answer is yes and zero otherwise. As described above, cooperating firms are more innovative as compared to isolated (non-cooperative) firms and it is more probable that they need to secure their knowledge as tradable asset, so they apply more often for patents. 144 of 317 (45.4%) firms for which there is an observation on cooperative behaviour reported having cooperated in R&D in the first three business years.

d. Scientific orientation

The variable *MeaningRes* measures the meaning of scientific insights for the development of the firm's product or service. It is derived from the question: *Which meaning had scientific insights and specific competencies of research institutes for the development of your product/service before the first business year? MeaningRes* ranges from one to five with one meaning 'completely unimportant' and five meaning 'very important'. The more important scientific findings are to the development of the business idea, the more innovative it is expected to be.

6.3.5 Controls

a. Product vs. Process firm

Product controls whether the firm is more devoted to offering products rather than services. This variable is derived from the question: *From which kind of output did you make the biggest share of your revenue*? This variable becomes one if the firm made the most of its revenue from a product and zero if it made it from a service or from a product and service equally. Product innovations are easier to patent than service innovations. Therefore firms offering products may have a higher propensity to patent and the number of patents applied for may be higher (Hall et al. 2012).

b. Scientific education of the founder(s)

Persons having a PhD already have experience in R&D and may also intrinsically be devoted to innovations and patenting such that those persons in the founding team may carry out more patenting activity than those with a university degree as their highest degree. The variable measuring the share of founders with a PhD in the founding team is *Sh.Founders.PhD*. It can be expected that a higher proportion of founders with PhDs signals a higher technological level in the firm. This may be combined with a higher degree of innovativeness and thus patenting activity.

c. Team size

The more founders in the team, the more likely it is that one of them will have an idea that is patentable. Thus, the number of founders (*No.Founders*) is used as control variable in the respective estimations.

d. Spin-off

It has been found for this database that spin-offs have a higher propensity to patent (Cantner and Göthner 2011). Thus, the variable *Spin-off* is a binary variable, measuring whether the firm is a spin-off of a firm, university or research institute or not.

e. Patent intensive sector

As described in section 6.3.1 of this paper, the sample has already been selected into the direction of innovative industries such as 'advanced technology' and 'technology-oriented services' according to the ZEW classification (Grupp et al., 2000). However, in the questionnaire the interviewed founders could assign their firm to one of the seven sector categories. Since biotechnology, pharmaceuticals and chemicals have been found in earlier studies to be quite patent intensive (e.g. Bound et al. 1984), the dummy variable *BioChem* has been created to control for these patent intensive sectors.

f. Jena

The city of Jena can be said to be the innovative centre of the small German federal state Thuringia and it has the only University in Thuringia with so called ‘Promotionsrecht’, which is the admission to grant doctoral degrees. Thus, it may be the case that this region drives the result found in the estimations even more than the patenting itself. The dummy variable *Jena* is therefore used in order to control for this.

Table 6-2 depicts the correlations between all variables used in the analysis.

6.4 Results

This section presents and discusses the results of the empirical analysis. Before doing this, however, some remarks concerning the control variables have to be made. First, the variable *Product* which is measuring whether the firm is offering products rather than services becomes significant over all estimations where it is included. Here a positive correlation with the number of patents applied for in the first three business years can be found. Thus, the former findings by Hall et al. (2012) can be supported; products are easier to patent than services.

The second control variable *No.founders* representing the size of the founding team is in one of the estimations significant and positive. Thus, the results hint in the expected direction: the more founders a firm has, the higher the probability is that they come to patentable ideas.

The dummy variable *Jena* has been included since a bias towards this region could have been expected. However, the estimations show that Jena has a significant but negative relationship with the number of patents applied for in the first three business years. This result is quite unexpected. It would mean, compared to all other regions in Thuringia, firms in Jena on average patent less. Since the number of patents a firm applies for is extremely skewed to the left and only 4% of the firms apply for more than five patents, the probability that these firms come from Jena is quite small, which may explain the unexpected finding.

The educational background of the founders (*Sh.Founders.PhD*), spin-offs (*Spinoff*) and the dummy for the most patent intensive sectors in the sample, namely biotechnology, pharmaceuticals and chemicals (*BioChem*), do not show any significant relation to the number of patents applied for in the first three business years.

6.4.1 Pre-founding phase

It has been argued earlier in this paper that patenting activities may be path dependent such that patenting carried out by the founders in the pre-founding phase may be positively related to patenting during the firms' business life. Table 6-3 shows the results.

For all estimations, patenting before founding the firm shows a positive and significant correlation with the number of patents applied for (patenting intensity). For all estimations, the observed coefficient ranges around 1.4. This indicates that the expected number of patents applied for by firms whose founders have already patented before starting it up is exp(1.4)=4.06 times the expected number of patents applied for by firms whose founders do not have patenting experience. Hypothesis 6-1, stating that patenting is path dependent in the sense that if it is pursued during the process of preparing to found the firm, this increases the patenting intensity after the firm has been launched, can therefore not be rejected.

Table 6-1 Variables used for the analysis of the propensity to patent of young and innovative firms

Use	Variable	Description	Obs	Mean	Std. Dev.	Min	Max
Dependent Variable	*No.Patents*	Number of Patents a firm applied for in the first three business years.	534	0.4064	1.5931	0	16
H6-1	*PatentsBefore*	Dummy variable, indicating whether the founders were already active in patenting before founding the firm (1) ot not (0).	534	0.0880	0.2836	0	1
H6-2	*statepromotion*	Dummy variable which indicates whether the firm received R&D promotion in the first three business years (1) or not (0).	534	0.2116	0.4088	0	1
H6-3	*VentureCapital*	Dummy variable is 1 if the firm received venture capital at the beginning of its first three business years and 0 otherwise.	364	0.0577	0.2335	0	1
H6-4	*Cooperation*	Dummy variable which indicates whether the firm cooperated in R&D in the first three business years (1) or not (0).	317	0.4543	0.4987	0	1
H6-5	*ScienceOrientation*	Five digit variable, indicating the meaning of scientific insights and specific competencies of research institutes for the development of the firms' product or service.	447	2.5615	1.5932	1	5
Controls	*Products*	Dummy variable, indicating whether the firm is more devoted to products (1) or services (0).	387	0.3850	0.4872	0	1
	Sh.Founders.PhD	Share of founders holding a PhD.	473	0.1024	0.2529	0	1
	No.Founders	Total number of founders.	534	2.1479	1.1156	1	5

Table 6-1 continued

Use	Variable	Description	Obs	Mean	Std. Dev.	Min	Max
Dependent Variable	*No.Patents*	Number of Patents a firm applied for in the first three business years.	534	0.4064	1.5931	0	16
Controls	*Spinoff*	Dummy variable, indicating whether the firm is an academic spin-off (1) or not (0).	534	0.2228	0.4165	0	1
	BioChem	Dummy variable indicating whether the founders allocate their firm to the sector of biotechnology, pharmaceuticals and chemicals (1, zero otherwise).	532	0.0320	0.1760	0	1
	Jena	Dummy variable indicating whether the firm is located in Jena (1) or elsewhere in Thuringia (0).	534	0.1255	0.3316	0	1
	R&DpreFounding	Dummy variable, indicating whether the founders already conducted R&D in the preparation process of their firm founding.	532	0.4211	0.4942	0	1

Table 6-2 Correlation between the variables used for estimating the propensity to patent of young firms

		1	2	3	4	5	6	7	8	9	10	11	12
1	*No.Patents*	1											
2	*PatentsBefore*	0.4938*	1										
3	*R&Dpromotion*	0.1694*	0.1156*	1									
4	*VentureCapital*	0.0021	-0.0031	-0.1212	1								
5	*Cooperation*	0.2083*	0.1459*	0.1512*	0.0188	1							
6	*ScienceOrientation*	0.2247*	0.2243*	0.2438*	0.0083	0.2730*	1						
7	*Products*	0.1875*	0.1631*	0.2401*	0.0738	0.0344	0.0514	1					
8	*Sh.Founders.PhD*	0.1961*	0.1242*	0.1616*	0.0234	0.2229*	0.2776*	-0.0128	1				
9	*No.Founders*	0.1632*	0.1588*	0.1656*	-0.0096	0.1352*	0.1617*	0.0392	0.0838	1			
10	*Spinoff*	0.1551*	0.1278*	0.1071*	-0.0106	0.1243*	0.1389*	-0.0474	0.1700*	0.2218*	1		
11	*BioChem*	0.1041*	0.1199*	0.0957	0.1578*	0.0622	0.1254*	0.0761	0.2197*	0.0359	0.0487	1	
12	*Jena*	0.1143*	0.1102*	0.1458*	0.0491	0.073	0.0982*	0.0251	0.0794	0.1465*	0.1017*	0.0498	1

*p<=.05

6.4.2 Business life

a. R&D promotion

R&DPromotion is a binary variable, indicating that a firm received public R&D support. In table 6-3 the coefficient for this variable becomes significant and positive for all estimations, indicating that there is a positive correlation between receiving this kind of state promotion and the patenting intensity of start-ups. More specifically, the expected number of patents applied for by firms which have received state promotion would be exp(0.96)=2.65 times the expected number of patents applied for by firms without state promotion. Hypothesis 6-2 stating that start-ups that receive state promotion have higher patenting intensities cannot be rejected.

b. Venture Capital

Hypothesis 6-3 says that start-ups with a venture capital budget can more easily apply for patents and will therefore patent more. The respective variable *VentureCapital* does not show any significant relation to the dependent variable, namely the number of patents applied for, which leads to a rejection of hypothesis 6-3.

c. Cooperation

Looking at the results in table 6-3, cooperation in R&D has a significant positive correlation with effect on the number of patents applied for and this finding is stable over three of the four models. The expected number of patents applied for by cooperative firms is about exp(1)=2.72 times the expected number of patents applied for by non-cooperative firms. This finding also fits to earlier studies on the positive effect of cooperation on innovativeness (Cowan et al. 2006). Cooperating firms are more frequently successful in creating innovations and thus apply more frequently for patents as compared to isolated (non-cooperative) firms. Thus, hypothesis 6-4 indicating that cooperation positively relates to patenting activities cannot be rejected.

d. Scientific orientation

The variable indicating a firms' scientific orientation is *ScienceOrientation,* which comprises the meaning of scientific insights for the development of the firm's product or service. Significant and positive results have been found in models 1 and 3 such that hypothesis 6-5, indicating that firms conducting R&D and basing their activities on scientific insights patent more, cannot be rejected. However, this effect seems to be related to the region of Jena since no significant result can be found if the dummy (*Jena*) is excluded.

6.4.3 Inflation parameter

Since the excess zeros in the outcome variable *No.Patents* can be the result of unsuccessful R&D or no R&D at all, R&D activities in the three years before the firm was started-up have been taken as inflation variable. However, the results in table 6-3 show that there is no significant correlation between research activities before the start-up is launched and the number of patents applied for in the first three business years.

Table 6-3 What influences the propensity to patent for young firms?

Method	Zero-inflated negative binomial regression							
Depvar	*No.Patents*							
	model 1		model 2		model 3		model 4	
PatentsBefore	1.3212	***	1.7124	***	1.3011	***	1.3291	**
	(3.03)		(2.93)		(3.03)		(2.24)	
R&Dpromotion	1.1281	**	0.7660	*	1.0791	**	0.9418	*
	(2.33)		(1.90)		(2.46)		(1.77)	
VentureCapital	0.1975		-0.5539		0.2499		-0.1478	
	(0.34)		(-0.77)		(0.47)		(-0.17)	
Cooperation	0.8804	**	1.2656	***	0.8704	**	0.5399	
	(2.41)		(3.28)		(2.41)		(1.24)	
ScienceOrientation	0.2108	*	0.1417		0.2111	*	0.1074	
	(1.65)		(1.04)		(1.66)		(0.58)	
Products	1.0822	*			1.0817	*	1.2691	**
	(1.70)				(1.71)		(2.16)	
Sh.Founders.PhD	-0.9912				-0.9881		-0.4543	
	(-1.62)				(-1.61)		(-0.39)	
No.Founders	0.2230				0.2052	*	0.2095	
	(1.58)				(1.69)		(1.24)	
Spinoff	-0.0882						0.0907	
	(-0.24)						(0.21)	
BioChem	0.7940				0.2052		0.7344	
	(0.54)				(0.58)		(0.26)	
Jena	-1.1630	***			-1.1476	***		
	(-3.30)				(-3.30)			
Constant	-2.6805	***	-2.0586	***	-2.6396	***	-2.5995	***
	(-4.29)		(-3.03)		(-4.41)		(-3.83)	
Inflate								
R&DpreFounding	-0.1999		-1.0375		-0.2072		-0.2618	
	(-0.28)		(-1.30)		(-0.29)		(-0.33)	
Constant	0.2372		0.5633		0.2478		0.0609	
	(0.35)		(0.57)		(0.37)		(0.07)	
No. of Obs.	114		185		114		114	
Zero Obs	88		150		88		88	
Prob>Chi	0.0000		0.0000		0.0000		0.0001	
/lnalpha	-19.5512		0.1444		-15.659		-1.6621	
	(-0.03)		(0.13)		(-0.02)		(-1.07)	
alpha	0.0000		1.1553		0.0000		0.1897	

Robust z statistics in parentheses

*significant at 10%, **significant at 5%, ***significant at 1%

6.5 Conclusions

In this paper, economic information as well as information about the socio-demographic and psychological profiles of the founders of 534 young firms operating in innovative industries has been analysed. The aim was to find out which factors are related to the propensity to patent in the form of the number of patents applied for by the group of young enterprises and in this way to assess the validity of patent data as measurement of innovative and cooperative activities. Contrasting with earlier studies e.g. by Hall et al. (2013), this paper identifies a start-up's patents by taking applications made by the founders into account. Descriptive analyses have shown that only about 5.5% of start-up patents are applied for under the name of the firm. Thus, the undercounting of young and innovative firms' patenting activity in other studies e.g. in the above-mentioned may have been avoided here.

Regarding the whole database, it emerges that while 60.53% (322) of the firms report conducting R&D in the first three business years, 64 firms (19.88%) applied for patents. Arundel and Kabla (1998) find that 35.9% of product innovations are patented which would mean that the share of patenting firms among those conducting R&D should be around 36%. Since they analyse Europe's largest industrial firms and this paper's analysis looks at Thuringia's smallest firms (although the results are by no means comparable) it shows that on a comparative basis small firms seem to have a relatively high rate of patenting (20%) and that this can be detected more easily if the proposed procedure of identifying small firm's patents is applied, as in this paper.

It emerges that the main factors governing small firms' patent applications are 'patents before the firm founding', 'state promotion', scientific orientation' and 'cooperation'.

Regarding the pre-founding patenting behaviour, this paper's analysis detects a path dependency that goes in the direction of the success-breeds-success hypothesis formulated by Dosi et al. (1997). When founders have already conducted R&D and applied for patents in the nascent phase, they will also go on patenting after starting up the business. If patenting is considered a factor of success, policymakers should not ignore this relationship and include this indicator when considering funding for young and innovative firms. Additionally, cooperation in R&D seems to support innovative success.

R&D promotion is also positively connected to patenting activities. As Cantner and Kösters (2009) argue, R&D support from the state may promote patenting activities for two reasons. Firstly, firms receiving such support have more financial scope and secondly, referees have evaluated the innovativeness of their business idea such that their patenting propensity may also be higher. When taking patents as an indicator of innovative success, the finding that state promotion positively influences patenting can be taken as a sign of successful state programmes.

Cooperation serves as a vehicle for the formalisation of technology exchange agreements (Brouwer and Kleinknecht 1999) and, following the arguments of the resource-based-view of the firm (Penrose 1959), they have a positive effect on firms' innovativeness (Cowan et al. 2006) such that cooperative firms may have a higher propensity to be active in patenting. The results for small and innovative start-ups in this paper indicate this. Policymakers thinking about programmes to enhance innovativeness in start-ups may therefore consider financial support for cooperative R&D projects.

The result that the scientific orientation or otherwise of the firms' R&D activities plays a role in patenting activity suggests that researchers should consider what kind of firms are in the sample if they analyse patent data. Taking all the findings together, one may argue that, when using patents as indicator for innovation or cooperation, one has to be aware of the fact that only the science-oriented ones, conducting R&D in advance and having R&D cooperation when the firm is founded are taken into account among all start-ups. However, although it has been argued that small firms may be a group of their own (Hall et al. 2012) and that different laws may govern the groups of small firms and larger firms (Bound et al. 1984), the findings suggest that small firm patenting behaves in basically the same way as larger firm patenting. It is past success in patenting, cooperation and orientation towards the latest scientific insights that drives innovative start-up patenting.

Unfortunately, this study has some drawbacks that may be solved by future research. First, the firm database contains only Thuringian firms, which only represent a small part of Germany. Thus, it could be argued that future analyses should conduct a regionally broader analysis. However, a look at the maps created by Aamoucke and Fritsch (2013) shows that Thuringia is representative of most of Germany with respect to the average yearly number of start-ups in

technology-oriented industries. This indicates the worthiness of the analysis, particularly for political decision-making.
Second, this analysis has been carried out under the assumption that all the firms have the same strategic reason for patenting, which is mainly the reputation effect (Hall et al. (2012)). Unfortunately, such a question was missing in the questionnaire provided by the Thuringian Founder Study. In future questionnaires, this kind of item should be included.

7. Conclusions of the thesis

Since each my chapters presents its own conclusion, I want to keep the closing remarks of my dissertation as short and non-redundant as possible and put the dissertation into a wider perspective.

Before the occurrence of the industrial revolution, the economy was characterized by a very long period of stagnation (Bairoch 1993). In fact, Bairoch (1993) argues that in the last 700 years before the industrial revolution was born, the economy grew about 2% in an optimistic calculation. In comparison, for the 290 years after 1700, he finds a growth rate of about 45%. The world we live in today is the result of this industrialization process which started around 1760 in the United Kingdom. An agricultural revolution which began in 1660 had led to changes in the demand for new materials, breeds, and transportation which has been satisfied by new technologies (innovation). Since then the world has changed dramatically, labor has been organized differently and the economy became a complex system which is neither easy to understand nor to predict. The first scholars that found theories to explain economic development were Adam Smith (1976), David Ricardo (1817) and Karl Marx (1967). Schumpeter (1912) was the first to announce creative destruction caused by innovation as the main driver of economic growth. In response to the growth model of Solow (1956) which sees technological change as something exogenous that falls like *manna from heaven*, Nelson and Winter (1982) introduced their Neo-Schumpeterian view on economic growth and built the foundation of modern evolutionary theorizing on growth. In their theory, entrepreneurs or institutionalized R&D activities destroy existing market equilibria via innovation leading to economic growth. This means that innovation happens at the firm level, which is an absolutely micro-based view on economic development. Until today, many researchers tried to formally model the economic growth process but still there is no definite model of the processes. Additionally, the most pressing economic problems of today, like slowing growth and innovation rates, inequality, unemployment and economic crisis can only be solved if the evolutionary mechanisms of growth are fully understood. My dissertation adds to the understanding of these mechanisms by analyzing the micro behavior of entrepreneurs and firms that pursue institutionalized R&D. In the knowledge-based economy, innovation cannot be produced without interactions and cooperation between agents. What I am looking at is, therefore, the role cooperation and knowledge exchange play for the success and failure of innovative firms. As argued above, by introducing innovation to the market, these firms push the economy out of its temporal (equilibrium) and lead to evolutionary economic growth. If we learn more about how interaction and knowledge networks influence their behavior, we might make a step further in understanding this kind of growth.

Chapters 2 and 3 of this dissertation look at the determinants of cooperation dynamics. While chapter 2 finds that cooperation is not pursued if the costs of finding a partner are too high and that cooperation break-up is very often the result of trust problems, chapter 3 shows that dynamics in cooperation relationships are a quite common feature and that many changes in the partner can even be favourable under the right circumstances. Chapters 4 and 5 go one step further and analyze the role of the regional innovator network for the success and failure of entrepreneurial ventures. The analyses show that the size and density of the network as such as well as central position in the network help firms in keeping competitive advantages and staying in the market, but this seems to be dependent of the stages in the organizational life cycle. Chapter 6 is more devoted to the questions, how to identify patents for entrepreneurial ventures and what the determinants of their patenting behavior are. I find that when analyzing innovation of young and innovative ventures by patents, it is crucial to add the patents applied for in the name of the founders to the firm's patents.

How can the results be helpful for evolutionary models of economic growth? After Nelson and Winter (1982) lots of research was devoted to the modeling of evolutionary growth (e.g. Dosi and Fabiani 1994, Silverberg and Verspagen 1995/1998). These models also consider behavioral aspects as one factor entering into this analysis. The research done in this dissertation analyzed two interrelated aspects of the micro behavior of firms, namely R&D cooperation and innovative networks. It has been shown that dynamics of cooperative relationships and networks are important and positive for firm success. Therefore, the knowledge about the impact of these interactions should be also used and integrated into the analysis of evolutionary models for economic growth as one feature of behavioral differences among firms.

After proposing to use the first insights this dissertation gave on the role of interaction and social scientific networks on the success and failure of innovative firms in models of evolutionary growth, also some policy implication might be drawn from this work. From chapters 2 and 3 one could conclude that on the one side a good intermediation infrastructure would help in getting more firms into cooperation. Additionally, a very clear and easy to dispose of a system of intellectual property rights, maybe even consulting agencies for this purpose would prevent a cooperation break-off for the reason of trust problems. However, dynamics of cooperation is not at all negative and should not be taken as bad characteristic if selecting firms for cooperative R&D funding.
Chapters 4 and 5 go one step further and analyze the role of the regional innovator network for the success of entrepreneurial firms. If a policy maker is about to choose firms to fund, this social connection aspect should be taken into account. According to chapter 6, the tendency of founders of young and innovative firms to apply for patents on their own names rather than on the name of the firms should also be taken into account by policy makers when they have to make funding decisions.

For sure, this dissertation leaves open room for future research. As for chapter 2, it would be interesting to analyze the determinants of cooperation failure in more detail and to use a specialized questionnaire only for this kind of question. Additionally, it would be interesting to see how the determinants of cooperation failure develop over time, meaning that the analysis should be repeated in a panel setting. In chapter 3 my co-authors and I are stepping into a research stream which is still in its infancy, the dynamic analysis of networks. In the future, these models will be refined and developed further such that the analysis could maybe be repeated with more appropriate empirical methods. As for the analysis of the social scientific network of firm founders and their influence on the success of their firms, on could also analyze the networks with respect to a technological framework. This might be questions like: Is it more favorable to be connected to a technologically fragmented network or is the firm positively influenced by specialized networks?

Bibliography

Aamoucke, R., Fritsch, M. (2013): Regional Knowledge and Innovative Start-ups – An Empirical Investigation, Small Business Economics, 41, 865-885. doi: 10.1007/s11187-013-9510-z.

Acs, Z., Audretsch, D. (1990): Innovation and Small Firms, MIT Press, Massachusetts.

Ahuja, G. (2000): Collaboration networks, structural holes, and innovation: A longitudinal study, Administrative Science Quarterly, 45, 425-455. doi:10.2307/2667105

Aldrich, H. E. (1999): Organizations Evolving, London: SAGE.

Aldrich H. E., Reese, P. R. (1993): Does networking pay off? A panel study of entrepreneurs in the research triangle. In: Churchill, N. et al. (eds): Frontiers of Entrepreneurship Research, Babson College: Babson, MA; 325–399.Allen, R. (1983): Collective invention, Journal of Economic Behavior and Organization 4: 1-24.
doi:10.1016/0167-2681(83)90023-9

Anthonisse, J. M. (1971): The Rush in a Graph, Amsterdam: Mathematisch Centrum.

Arundel, A., Kabla, I. (1998): What percentage of innovations are patented? empirical estimates for European firms, Research Policy, 27 (2), 127–141.
doi:10.1016/S0048-7333(98)00033-X

Arundel, A. (2001): The relative effectiveness of patents and secrecy for appropriation, Research Policy, 30 (4), 611 – 624.
doi:10.1016/S0048-7333(00)00100-1

Asheim, B., Isaksen, A. (2002): Regional innovation systems: the integration of local sticky and global ubiquitous knowledge. Journal of Technology Transfer, 27, 77-86.
doi: 10.1023/A:1013100704794

Asheim, B. T., Gertler, M. S. (2005): The geography of innovation: Regional innovation systems. In: J. Fagerberg, D. Mowery, R. Nelson (Eds.), The Oxford handbook of innovation (pp. 291-317). Oxford, UK: Oxford University Press.
doi:10.1093/oxfordhb/9780199286805.003.0011

Audretsch, D. B. (1995): Innovation and Industry Evolution, MIT Press, Massachusetts.

Audretsch, D. B., Feldman, M. P. (2004): Knowledge spillovers and the geography of innovation. In J. V. Henderson, J. F. Thisse (Eds.): Handbook of regional and urban economics (Vol. 4, pp. 2713–2739). Elsevier: Amsterdam.

Audretsch, D.B., Lehmann, E.E. (2005): Does the Knowledge Spillover Theory of Entrepreneurship Hold for Regions?, Research Policy, 34, 1191-1202. doi:10.1016/j.respol.2005.03.012

Balconi, M., Breschi, S., Lissoni, F. (2004): Networks of inventors and the role of academia: an exploration of Italian patent data, Research Policy, 33, 127-145.
doi:10.1016/S0048-7333(03)00108-2

Bairoch, P. (1993): Economics & World History: Myths and Paradoxes, University of Chicago Press.

Balland, P.-A., Boschma, R., Frenken, K. (2015): Proximity and innovation: From statics to dynamics. Regional Studies, 49, 907-920.
doi:10.1080/00343404.2014.883598

Balland, P.-A., de Vaan, M., Boschma, R. (2013): The dynamics of interfirm networks along the industry life cycle: The case of the global video games industry, 1987-2007. Journal of Economic Geography, 13, 741-765.
doi:10.1093/jeg/lbs023

Barabási, A.-L., Albert, R. (1999): Emergence of scaling in real networks. Science, 286, 509-512.
doi:10.1126/science.286.5439.509

Bartelsman, E., Scarpetta, S., Schivardi, F. (2005): Comparative analysis of firm demographics and survival: evidence from micro-level sources in OECD countries, Industrial & Corporate Change, 14, 365-391. doi:10.1093/icc/dth057

Baum, J. C. A. (1996): Organizational Ecology. In: Clegg, S., Hardy, C., Nord, W. (eds): Handbook of Organization Studies, Sage, London, 77-114.

Baum, J., Calabrese, T., Silverman, B. (2000): Don't go it alone: Alliance network composition and startups' performance in Canadian biotechnology, Strategic Management Journal, 21, 267-294.
doi: 10.1002/(SICI)1097-0266(200003)21:3<267::AID-SMJ89>3.0.CO;2-8

Bayona, C., Garcia-Marco, T., Huerta, E. (2001): Firms' motivation for cooperative R&D: an empirical analysis of Spanish firms, Research Policy, 30, 1289-1307.
doi:10.1016/S0048-7333(00)00151-7
Beauchamp, M. A. (1965): An improved index of centrality, Systems Research and Behavioral Science, 10, 161-163.
doi: 10.1002/bs.3830100205
Beaudry, C., Schiffauerova, A. (2011): Impacts of collaboration and network indicators on patent quality: The case of Canadian nanotechnology innovation. European Management Journal, 29, 362-376.
doi:10.1016/j.emj.2011.03.001
Belderbos, R., Carree, M., Lokshin, B. (2004): Cooperative R&D and firm performance, Research Policy, 33, 1477–1492.
doi: 10.1016/j.respol.2004.07.003
Benner, M., Waldfogel, J. (2008): Close to you? Bias and precision in patent-based measures of technological proximity. Research Policy, 37, 1556-1567.
doi:10.3386/w13322
Blind, K., Edler, J., Frietsch, R., Schmoch, U. (2006): Motives to patent: Empirical evidence from Germany, Research Policy, 35 (5), 655 – 672.
doi:10.1016/j.respol.2006.03.002
Bonacich, P. (1972): Factoring and weighting approaches to clique identification, Journal of Mathematical Sociology, 2, 113-120.
Stable url: http://dx.doi.org/10.1080/0022250X.1972.9989806
Boschma, R. A. (2005): Proximity and innovation: A critical assessment. Regional Studies, 39, 61–74.
doi:10.1080/0034340052000320887
Boschma, R. A., Frenken, K. (2010): The spatial evolution of innovation networks: A proximity perspective. In R. Boschma, R. Martin (Eds.), The handbook of evolutionary economic geography (pp. 120-136). Cheltenham, UK: Edward Elgar.
doi:10.4337/9781849806497.00012
Bound, J., Cummins, C., Griliches, Z., Hall, B., Jaffe, A. (1984): Who does R&D and who patents?: NBER Working Paper No. 908.
doi: 10.3386/w0908

Breschi, S., Lissoni, F. (2006): Cross-firm inventors and social networks: Localized knowledge spillovers revisited, Annules d'Economie et de Statistique, 79-8.
Stable url: http://www.jstor.org/stable/20777575

Broekel, T. (2015): The co-evolution of proximities—A network level study. Regional Studies, 49, 921–935.
doi:10.1080/00343404.2014.1001732

Broekel, T., Balland, P.-A., Burger, M., van Oort, F. (2014): Modeling knowledge networks in economic geography: A discussion of four empirical strategies. The Annals of Regional Science, 53, 423-452.
doi:10.1007/s00168-014-0616-2

Broekel, T., Boschma, R. (2012): Knowledge networks in the Dutch aviation industry: The proximity paradox. Journal of Economic Geography, 12, 409-433.
doi:10.1093/jeg/lbr010

Brouwer, E., Kleinknecht, A. (1999): Innovative output and a firms' propensity to patent: An exploration of CIS micro data, Research Policy, 28 (6), 615 – 624.
doi:10.1016/S0048-7333(99)00003-7

Brown, S.L., Eisenhardt, K.M. (1997): The art of continuous change: linking complexity theory and time-paced evolution in relentlessly shifting organizations, Administrative Science Quarterly, 42, 1-34.
Stable url: http://www.jstor.org/stable/2393807

Burt, R.S. (1992): Structural Holes. Cambridge, MA: Harvard University Press.

Cameron, A.C., Trivedi, P.K., (2013): Regression Analysis of Count Data. 2nd edition, Cambridge Univ. Press, Cambridge, UK.

Cantner, U. (2000): Die Bedeutung von Innovationssystemen für die internationale Wettbewerbsfähigkeit. In: Staroske, U., Wiegand-Kottisch, M., Wohlmuth, K. (eds), Innovation als Schlüsselfaktor eines erfolgreichen Wirtschaftsstandortes. Lit Verlag.

Cantner, U., Helm, R., Meckl, R. (2003): Innovationssysteme aus volks- und betriebswirtschaftlicher Perspektive: Bedeutung und Strukturen. In: Cantner, U., Helm, R., Meckl, R. (eds), Strukturen und Strategien in einem Innovationssystem – Das Beispiel Jena. Verlag Wissenschaft and Praxis.

Cantner, U., Graf, H. (2003): Innovationssysteme und kollektive Innovationsprozesse: Einige theoretische Grundlagen. In: Cantner, U., Helm, R., Meckl, R. (eds), Strukturen und Strategien in einem Innovationssystem – Das Beispiel Jena. Verlag Wissenschaft and Praxis.

Cantner, U., Graf, H. (2006): The network of innovators in Jena: An application of social network analysis. Research Policy, 35, 463-480. doi:10.1016/j.respol.2006.01.002

Cantner, U., Graf, H., (2007): Growth, Development and Structural Change of Innovator Networks – The Case of Jena, Jena Economic Research Papers, #2007-090.
Last time retrieved June 7, 2016, from: http://zs.thulb.uni-jena.de/servlets/MCRFileNodeServlet/jportal_derivate_00085907/wp_2007_090.pdf

Cantner, U., Meder, A. (2007): Technological proximity and the choice of cooperation partners. Journal of Economic Interaction and Coordination, 2, 45-65. doi:10.1007/s11403-007-0018-y

Cantner U., Meder, A., Wolf, T. (2008): Intermediation, reciprocity and compatibility in regional innovation systems – an interregional comparison, 2008, Jena Economic Reserach Papers, 2008-081.
Stable url: http://EconPapers.repec.org/RePEc:jrp:jrpwrp:2008-081

Cantner, U. and Kösters, S. (2009): R & D Subsidies to Start-ups – Effective Drivers of Patent Activity and Employment Growth?, Jena Economic Research Papers, 2009-027, 2009.
Last time retrieved June 8, 2016, from: http://zs.thulb.uni-jena.de/servlets/MCRFileNodeServlet/jportal_derivate_00169879/wp_2009_027.pdf

Cantner, U., Conti, E., Meder, A. (2010): Networks and innovation: The role of social assets in explaining firms' innovative capacity. European Planning Studies, 18, 1937-1956.
doi:10.1080/09654313.2010.515795

Cantner, U., Goethner, M., Stuetzer, M. (2010): Disentangling the effects of new venture team functional heterogeneity on new venture performance, Jena Economic Research Papers, 2010-29.
Last time retrieved October 21, 2016 from: http://pubdb.wiwi.uni-jena.de/pdf/wp_2010_029.pdf

Cantner, U., Graf, H. (2011): Innovation networks: Formation, performance and dynamics. In Antonelli, C. (Ed.), Handbook on the economic complexity of technological change (pp. 366–394). Cheltenham, UK: Edward Elgar.

Cantner, U., Göthner, M. (2011): Performance differences between academic spin-offs and non-academic start-ups: an empirical investigation, Presented at the DIME Final Conference 2011, Maastricht.
Last time retrieved June 8, 2016, from: http://final.dime-eu.org/files/ Cantner_Goethner_D4.pdf

Cantner U., Meder, A., Wolf, T. (2011): Success and failure of firms' innovation cooperations: The role of intermediaries and reciprocity. Papers in Regional Science, 90, 313-329.
doi:10.1111/j.1435-5957.2011.00366.x

Cantner, U., Stuetzer, M. (2013): Knowledge and innovative entrepreneurship - social capital and individual capacities, in: Morone P. (Ed): Knowledge, Innovation and Internationalization, Essays in Honour of Cesare Imbriani (pp.59-90), Routledge. NY.

Cantner, U., Wolf, T., (2016): On regional innovator networks as hubs for innovative ventures, Jena Economic Research Papers, 2016-006.
Last time retrieved October 21, 2016 from: http://zs.thulb.uni-je.na.de/servlets/MCRFileNodeServlet/jportal_derivate_00245816/wp_2016_000.pdf

Caspi, A., Moffitt, T.E., Thornton, A., Freedman, D., et al (1996): The life history calendar: A research and clinical assessment method for collecting retrospective event-history data, International Journal of Methods in Psychiatric Research, 6 (2), 101 – 114.
ISSN: 1049-8931

Cassia, L., Colombelli, A., Pelari, S. (2009): Firm's growth: Does the innovation system matter?, Structural Change and Economic Dynamics, 20, 211-220.
doi:10.1016/j.strueco.2009.01.001

Churchill, N. C., Levis, V. L. (1983): The five stages of small business growth, Harvard Business Review, 61, 30-50.

Cialdini, R., Trost, M. (1998): Social influence: Social norms, conformity and compliance. In: Gilbert, G., Fiske, S., Lindzey, G. (eds), The Handbook of Social Psychology, Volume II. Oxford University Press.
Last time retrieved June 7, 2016, from: http://ocean.otr.usm.edu/~w535680/Cialdini%20&%20Trost%20%281998%29.pdf

Cohen, W. M., Levinthal, D. A. (1990): Absorptive capacity: A new perspective on learning and innovation. Administrative Science Quarterly, 35, 128-152.
Stable url: http://www.jstor.org/stable/2393553.

Coleman, J. S. (1988): Social Capital in the Creation of Human Capital, The American Journal of Sociology, 94, 95-120.
Stable url: http://www.jstor.org/stable/2780243

Cooke, P., Uranga, M. G., Etxebarria, G. (1997): Regional innovation systems: institutional and organisational dimensions, Research Policy, 1997, 26, 475-92.
doi:10.1016/S0048-7333(97)00025-5

Cordes, J.J., Hertzfeld, H.R., Vonortas, N.S. (1999): A survey of high technology firms,
Retrieved June 8, 2016 from: http://mail.sbaonline.sba.gov/advo/research/rs189tot.pdf.

Cowan, R., Jonard, N., Zimmermann, J.B. (2006): Evolving networks of inventors, Journal of Evolutionary Economics, 16, 155-174.
doi: 10.1007/s00191-005-0013-1

Cox, D.R. (1972): Regression Models and Life-Tables, Journal of the Royal Statistical Society B, 34, 2, 187-220.
Stable url: http://www.jstor.org/stable/2985181

Crépon, B., Duguet, E. (1997): Estimating the innovation function from patent numbers: GMM on count panel data, Journal of Applied Econometrics, 12 (3), 243 – 263.
doi: 10.1002/(SICI)1099-1255(199705)12:3<243::AID-JAE444>3.0.CO;2-4

Crescenzi, R., Gagliardi, L., Percoco, M. (2013): Social capital and the innovative performance of Italian provinces. Environment and Planning A, 45, 908-929.
doi:10.1068/a45221

Criscuolo, P., Salter, A., Ter Wal, A. (2010): Summer Conference 2010 on "Opening Up Innovation: Strategy, Organization and Technology": The role of proximity in shaping knowledge sharing in professional services firms. London, UK: Imperial College London Business School.

Czarnitzki, D., Hall, B. H., Oriani, R. (2006): Market valuation of US and European intellectual property. In: D. Bosworth & E. Webster (Eds.), The management of intellectual property (pp. 111-131). Cheltenham, UK: Edward Elgar.

Dahlander, L., McFarland, D. A. (2013): Ties that last: Tie formation and persistence in research collaborations over time. Administrative Science Quarterly, 58, 69-110.
doi:10.1177/0001839212474272

Davidsson, P. (2006): Nascent Entrepreneurship: Empirical Studies and Developments, Now Publishers Inc.

Dekker, D., Krackhardt, D., Snijders, T. A. B. (2007): Sensitivity of MRQAP tests to collinearity and autocorrelation conditions. Psychometrika, 72, 563-581.
doi:10.1007/s11336-007-9016-1

Diamond, D. (1984): Financial intermediation and delegated monitoring, Review of Economic Studies 51, 393-414.
doi: 10.2307/2297430

Doloreux, D., Parto, S. (2005): Regional innovation systems: current discourse and unresolved issues, Technology in Society, 27, 133-153.
doi:10.1016/j.techsoc.2005.01.002

Dosi, G. (1988): Sources, Procedures, and Microeconomic Effects of Innovation, Journal of Economic Literature, 26, 1120-1171.
Stable URL: http://www.jstor.org/stable/2726526

Dosi, G., Fabiani S. (1994): Convergence and Divergence in the Long-Term Growth of Open Economies'. In: Silverberg, G, Soete, L. (eds): The Economics of Growth And Technical Change: Technologies, Nations, Agents, E. Elgar

Dosi, G. (1997): Opportunities, incentives and the collective patterns of techonogical change, The Economic Journal, 107, 1530–1547.
doi: 10.1111/j.1468-0297.1997.tb00064.x

Dosi, G., Malerba, F., Marsili, O. and Orsenigo, L. (1997): Industrial Structures and Dynamics: Evidence, Interpretations and Puzzles, Industrial and Corporate Change, 6, (1), 3-24.
doi: 10.1093/icc/6.1.3

Edquist, C. (2005): Systems of innovation - perspectives and challenges. In: Fagerberg, J., Mowery, D., Nelson, R. (eds), The Oxford Handbook of Innovation. Oxford University Press.

Edwards, K.L., Gordon, T.J. (1984): Characterization of innovations introduced on the U.S. market in 1982, U.S. Small Business Economics No. SB-6050-0A-82.

Edworthy, E. Wallis, G. (2009): Research and Development as a Value Creating Asset. In OECD and FSO, Productivity Measurement and Analysis, OECD Publishing, Paris, 303-335.
doi: http://dx.doi.org/10.1787/9789264044616-16-en

Ejermo, O., Karlsson, C. (2006): Interregional inventor networks as studied by patent coinventorships, Research Policy, 35, 412–430.
doi:10.1016/j.respol.2006.01.001

Fagerberg, J. (2005): Innovation: A guide to the literature. In: Fagerberg, J., Mowery, D., Nelson, R. (eds), The Oxford Handbook of Innovation. Oxford University Press.

Falk, M., (2014): Corporate patents and knowledge sourcing from universities, Empirica, 41, 83-100.
doi: 10.1007/s10663-013-9226-y

Fehr, E., Gächter, S. (2000): Fairness and retaliation: The economics of reciprocity, Journal of Economic Perspectives, 14, 159-181.
doi: 10.1257/jep.14.3.159

Feldman, M. P., Audretsch, D. (1999): Innovation in cities: science-based diversity, specialization and localized competition, European Economic Review 43, 409-429.
doi: 10.1080/0042098002104

Fershtman, C., Gandal, N. (2011): Direct and indirect knowledge spillovers: the ‘social network’ of open source projects, RAND Journal of Economics, 42(1), 70-91.
doi: 10.1111/j.1756-2171.2010.00126.x

Freeman, L. C. (1977): A set of measures of centrality based on betweenness, Sociometry, 40, 35-41.
Last time retrieved October 21, 2016 from: http://moreno.ss.uci.edu/23.pdf

Freeman, C. (1987): Technology policy and economic performance: lessons from Japan. Pinter, London

Freeman, C. (1991): Networks of innovators: A synthesis of research issues. Research Policy, 20, 499-514.
doi:10.1016/0048-7333(91)90072-X

Gartner, W. B., Birs, B. J., Starr, J. A. (1992): Acting as if: differentiating entrepreneurial from organizational behavior, Entrepreneurship: Theory and Practice, 16, 13-31.
doi: 10.4337/9781783476947.00014

Gay, B., Dousset, B. (2005): Innovation and network structural dynamics: Study of the alliance network of a major sector of the biotechnology industry, Research Policy, 34, 1457–1475.
Stable url: http://dx.doi.org/10.1016/j.respol.2005.07.001

Gilsing, V., Nooteboom, B. (2005): Density and strength of ties in innovation networks: an analysis of multimedia and biotechnology, European Management Review, 2, 179–197.
doi: 10.1057/palgrave.emr.1500041

Gilsing, V., Nooteboom, B., Vanhaverbeke, W., Duysters, G., van den Oord, A. (2008): Network embeddedness and the exploration of novel technologies: Technological distance, betweenness centrality and density. Research Policy, 37, 1717-1731.
doi:10.1016/j.respol.2008.08.010

Giuliani, E. (2007): The selective nature of knowledge networks in clusters: Evidence from the wine industry. Journal of Economic Geography, 7, 139-168.
doi:10.1093/jeg/lbl014

Gnyawali, D. R., Madhavan, R. (2001): Cooperative networks and competitive dynamics: a structural embeddedness perspective, Academy of Management Review, 26, 431–445.
Stable url: http://www.jstor.org/stable/259186

Golden, P. A., Dollinger, M. (1993): Cooperative alliances and competitive strategies in small manufacturing firms, Entrepreneurship: Theory and Practice, 17, 43-56.
ISSN: 1042-2587
Gouldner, A. (1960): The norm of reciprocity: A preliminary statement, American Sociological Review, 25, 161-178.
Stable url: http://www.jstor.org/stable/2092623
Graham, S.J.H., Merges, R., Samuelson, P., Sichelman, T. (2010): High Technology Entrepreneurs and the Patent System: Results from the 2008 Berkley Patent Survey, Berkley Technology Law Journal, 24 (4), 1255 – 1328.
Stable url: http://ssrn.com/abstract=1429049
Graham, S.J.H., Sichelman, T. (2010): Why do Start-ups Patent?, Berkley Technology Law Journal, 23 (3), 1063 – 1097.
Stable url: http://ssrn.com/abstract=1121224
Granato, N., Farhauer, O. (2007): Die Abgrenzung von Arbeitsmarktregionen: Gütekriterien und Maßzahlen, Wirtschaftswissenschaftliche Dokumentation der TU Berlin. 2007/2.
Last time retrieved October 21, 2016 from:
https://www.econstor.eu/bitstream/10419/36434/1/526619074.pdf
Granovetter, M. (2005): The impact of social structure on economic outcomes. Journal of Economic Perspectives, 19, 33-50.
doi:10.1257/0895330053147958
Grant, R. M., Baden-Fuller, C. (1995): A knowledge-based theory of inter-firm collaboration. In: D.P. Moore (Ed.), Academy of Management Best Papers Proceedings 1995. 5th Annual Meeting of the Academy of Management, Vancouver, August 6-9, 1995 (pp. 17-21).
doi:10.5465/AMBPP.1995.17536229
Grant, R. M. (1996): Toward a knowledge-based theory of the firm, Strategic Management Journal, 17, 109-122.
doi: 10.1002/smj.4250171110
Greene, W.H. (2003): Econometric Analysis, fifth ed. Prentice Hall, New York
Griliches, Z. (1990): Patent statistics as economic indicators: A survey. Journal of Economic Literature, 28, 1661-1707.
doi:10.3386/w3301

Griliches, Z. (1992): Output measurement in the service sectors, NBER, Studies in Income and Wealth, Volume 56.
Last time retrieved October 21, 2016 from:
http://www.nber.org/chapters/c7230.pdf

Grupp, H., Jungmittag, A., Schmoch, U., Legler, H. (2000): Hochtechnologie 2000 - Neudefinition der Hochtechnologie für die Berichterstattung zur technologischen Leistungsfähigkeit Deutschlands, Karlsruhe/ Hannover.
Last time retrieved October 5, 2016, from:
http://publica.fraunhofer.de/eprints/urn_nbn_de_0011-n-36794.pdf

Gort, M., Klepper, S. (1982): Time Paths in the Diffusion of Product Innovations, The Economic Journal, 92, 630-653.
Stable url: http://www.jstor.org/stable/2232554

Güth, W., Kliemt, H., Napel, S. (2002): Wie du mir, so ich dir! - Ökonomische Theorie und Experiment am Beispiel der Reziprozität, Papers on Strategic Interaction, 19, Max-Planck-Gesellschaft.
Last time retrieved June 7, 2016, from: https://papers.econ.mpg.de/esi/discussionpapers/2002-19.pdf

Güth, W., Yaari, M. (1992): Explaining reciprocal behavior in simple strategic games: An evolutionary approach. In: Witt, U. (ed), Explaining Process and Change, Approaches to Evolutionary Economics, The University of Michigan Press.

Gulati, R. (1995): Does familiarity breed trust? The implications of repeated ties for contractual choice in alliances. Academy of Management Journal, 38, 85-112.
Retrieved April 7, 2015, from http://www.jstor.org/stable/256729

Gulati, R. (1999). Network location and learning: The influence of network resources and firm capabilities on alliance formation. Strategic Management Journal, 20, 397-420.
doi:10.1002/(SICI)1097-0266(199905)20:5<397::AID-SMJ35>3.0.CO;2-K

Gulati, R., Gargiulo, M. (1999): Where do interorganizational networks come from? American Journal of Sociology, 104, 1439-1493.
doi:10.1086/210179

Häusler, J., Hohn, H-W., Lütz, S. (1994): Contingencies of innovative networks: A case study of successful interfirm R&D collaboration, Research Policy, 23, 47-66.
doi: 10.1016/0048-7333(94)90026-4

Hagedoorn, J. (2002): Inter-firm R&D partnerships: An overview of major trends and patterns since 1960. Research Policy, 31, 477-492.
doi:10.1016/S0048-7333(01)00120-2

Hagedoorn, J., Frankort, H. T. W. (2008): The gloomy side of embeddedness: The effects of overembeddedness on inter-firm partnership formation. In: J. A. C. Baum, T. J. Rowley (Eds.), Network strategy (pp. 503-530). Advances in Strategic Management: Vol. 25. Binglay, UK: Emerald Group Publishing limited.
doi:10.1016/S0742-3322(08)25014-X

Hall, L.A., Bagchi-Sen, S. (2002): A study of R&D, innovation, and business performance in the Canadian biotechnology industry, Technovation, 22, 231–244.
doi:10.1016/S0166-4972(01)00016-5

Hall, B. H. (2007): Measuring the returns to R&D: The depreciation problem (NBER Working Paper No. 13473). Cambridge, MA: National Bureau of Economic Research.
doi:10.3386/w13473

Hall, B. H., Jaffe, A. B., Trajtenberg, M. (2001): The NBER Patent Citations Data File: Lessons, Insights and Methodological Tools (NBER Working Paper No. 8498). Cambridge, MA: National Bureau of Economic Research.
doi:10.3386/w8498

Hall, B. H., Helmers, C., Rogers, M., Sena, V. (2012): The choice between formal and informal intellectual property: a review, NBER Working Paper No. 17983.
doi: 10.3386/w17983

Hall, B. H., Helmers, C., Rogers, M., Sena, V. (2013): The importance (or not) of patents to UK firms, Oxford Economic Papers, Oxford University Press, vol. 65(3), pages 603-629.
doi: 10.3386/w19089

Hamel, G. (1991): Competition for competence and interpartner learning within international strategic alliances. Strategic Management Journal, 12(S1), 83-103.
doi:10.1002/smj.4250120908

Hanneman, R. A., Riddle, M. (2005): Introduction to social network methods, Riverside, CA: University of California.

Hargadon, A., Sutton, R. I. (1997): Technology brokering and innovation in a product development firm, Administrative Science Quarterly, 42, 716-749.
doi: 10.2307/2393655

Harhoff, D., Stahl, K., Woywode, M. (1998): Legal Form, Growth and Exit of West German Firms – Empirical Results for Manufacturing, Construction, Trade and Service Industries, The Journal of Industrial Economics, 46(4), 453-488.
doi: 10.1111/1467-6451.00083

Harter, J.F.R. (1994): The Propensity to Patent with Differentiated Products, Southern Economic Journal, 61 (1), 195 – 201.
Stable url: http://www.jstor.org/stable/1060141

Hausman, J.A., Hall, B.H., Griliches, Z. (1984): Econometric models for count data with an application to the patents–R&D relationship, Econometrica, 42 (4), 909–938.
doi: 10.2307/1911191

Heckman, J. J. (1981): Heterogeneity and State Dependence, NBER Chapters. In: S. Rosen (Ed.), Studies in labor markets (pp. 91-140). Chicago, IL: University of Chicago Press.

Heckmann, M., Schnabel, C, (2005): Überleben und Beschäftigungsentwicklung neu gegründeter Betriebe, Discussion Paper No. 39, Friedrich-Alexander-Universität Erlangen-Nürnberg.
Last time retrieved June 8, 2016, from: http://doku.iab.de/externe/2005/k051230f14.pdf

Heger, D., Zaby, A.K. (2012): Giving Away the Game? The Impact of the Disclosure Effect on the Patenting Decision, Centre for European Economic Research Discussion Paper No. 12-010.
Stable url: http://ssrn.com/abstract=2014677

Hite, J. M., Hesterly, W.S. (1999): The Evolution of Firm Networks: From emergence to Early Growth of the Firm, Strategic Management Journal, 22, 275-286.
doi: 10.1002/smj.156

Howells, J. R. L. (2002): Tacit Knowledge, innovation and Economic Geography, Urban Studies, 39, 871-884.
doi: 10.1080/00420980220128354

Hsu, D.H., Ziedonis, R.H. (2008): Patents as Quality Signals for Entrepreneurial Ventures, Academy of Management Proceedings, 2008:1, 1-6.
doi:10.5465/AMBPP.2008.33653924

Jaffe, A. (1986): Technological opportunity and spillovers of R&D: Evidence from firms' patents, profits and market value. American Economic Review, 76, 984-999.
doi:10.3386/w1815

Jaffe, A. B., Trajtenberg, M., Henderson, R. (1993): Geographic localization of knowledge spillovers as evidenced by patent citations. Quarterly Journal of Economics, 108, 577-598.
doi:10.2307/2118401

Kaplan, E. L., Meier, P. (1958): Nonparametric Estimation from Incomplete Observations, Journal of the American Statistical Association, 53, 282, 457-481.
Stable url: http://www.jstor.org/stable/2281868

Karlsson, C. (1997): Product development, innovation networks, infrastructure and agglomeration economies, The Annals of Regional Science, 31, 235-258.
doi: 10.1007/s001680050047

Katz, M.L., (1986): An analysis of cooperative research and development, Rand Journal of Economics, 17, 527–543.
Stable url: http://www.jstor.org/stable/2555479

Kennedy, P. (2009). A guide to econometrics (6th ed.). Cambridge, MA: Wiley-Blackwell.

Kessler, A., Frank, H. (2009): Nascent Entrepreneurship in a Longitudinal Perspective: The Impact of Person, Environment, Resources and the Founding Process on the Decision to Start Business Activities, International Small Business Journal, 27, 720-742.
doi: 10.1177/0266242609344363

Khanna, T., Gulati, R., Nohria, N. (1998): The dynamics of learning alliances: Competition, cooperation, and relative scope. Strategic Management Journal, 19, 193-210.
doi:10.1002/(SICI)1097-0266(199803)19:3<193::AID-SMJ949>3.0.CO;2-C

Kleinberg, J. M. (1999): Authoritative sources in a hyperlinked environment, Journal of the ACM, 46, 604-632.
doi: 10.1145/324133.324140

Kleinknecht, A. (1987): Measuring R&D in small firms: How much are we missing?, The Journal of Industrial Economics, XXXVI (2), 253 – 256.
doi: 10.2307/2098417

Kline, S.J., Rosenberg, N. (1986): An overview of innovation, in: R. Landau and N. Rosenberg (eds.): The positive sum strategy, (National Academy Press, Washington, DC) 275-305.

Kogut, B., Shan, W., Walker, G. (1992): The make or cooperate decision in the context of an industry network. In: N. Nohria, R. Eccles (Eds.), Networks and organizations: Structure, form, and action (pp. 348-365). Boston, MA: Harvard Business School Press.

Larson, A. L., Starr, J. A. (1993): A network model of organization formation, Entrepreneurship: Theory and Practice, 17, 5–15.
ISSN: 1042-2587

Lobo, J., Strumsky, D. (2008): Metropolitan patenting, inventor agglomeration and social networks: A tale of two effects, Journal of Urban Economics, 63(3), 871–884.
doi:10.1016/j.jue.2007.07.005

Lumpkin, G.T., Dess, G.G. (1996): Clarifying the entrepreneurial orientation construct and linking it to performance, Academy of Management Review, 21, 135-172.
Stable url: http://www.jstor.org/stable/258632

Lundvall, B. (1992): National Systems of Innovation: Towards a theory of innovation and interactive learning. Pinter.

March, J. G. (1991): Exploration and exploitation in organizational learning. Organization Science, 2, 71-87.
doi:10.1287/orsc.2.1.71

Marx, K. (1867): Das Kapital : Kritik der politischen Oekonomie. Hamburg: Verlag von Otto Meissner.

McKelvey, M. (1997): Coevolution in commercial genetic engineering. Industrial and Corporate Change, 6, 503-532.
doi:10.1093/icc/6.3.503

McPherson, M., Smith-Lovin, L., Cook, J. M. (2001): Birds of a feather: Homophily in social networks. Annual Review of Sociology, 27, 415-444.
doi:10.1146/annurev.soc.27.1.415

Meagher, K., Rogers, M. (2004): Network density and R&D Spillovers, Journal of Economic Behavior and Organization, 53, 237-260.
Stable url: http://dx.doi.org/10.1016/j.jebo.2002.10.004

Mowery, D. C., Oxley, J. E., Silverman, B. S. (1996): Strategic alliances and inter-firm knowledge transfer. Strategic Management Journal, 17, 77-91.
doi:10.1002/smj.4250171108

Mowery, D. C., Oxley, J. E., Silverman, B. S. (1998): Technological overlap and interfirm cooperation: Implications for the resource-based view of the firm. Research Policy, 27, 507-523.
doi:10.1016/S0048-7333(98)00066-3

Murray, F. (2004): The role of academic inventors in entrepreneurial firms: sharing the laboratory life, Research Policy, 33, 643–659.
Stable url: http://dx.doi.org/10.1016/j.respol.2004.01.013

Mwalili, S,. Lesaffre, E., Declerck, D. (2007): The zero-inflated negative binomial regression model with correction for misclassification: an example in caries research, Statistical Methods in Medical Research, 1 – 17.
doi: 10.1177/0962280206071840

Nelson, R., Winter, S. (1982): An Evolutionary Theory of Economic Change, HUP.

Nelson, A. J. (2009): Measuring knowledge spillovers: What patents, licenses and publications reveal about innovation diffusion, Research Policy, 38, 994-1005.
doi:10.1016/j.respol.2009.01.023

Nijkamp, P. (2011): Entrepreneurship, Development and the Spatial Context: Retrospect and Prospectsin: Naudé, W. (ed): Entrepreneurship and Economic Development, Studies in Development Economics and Policy, Palgrave Macmillan UK.
doi: 10.1057/9780230295155_13

Nomaler, Ö., Verspagen, B. (2008): Knowledge flows, patent citations and the impact of science on technology. Economic Systems Research, 20, 339-366.
doi:10.1080/09535310802551315

Nooteboom, B., (1998): Cost, quality and learning based governance of buyer-supplier relations. In: M. G. Colombo (Ed.), The changing boundaries of the firm (pp. 187-208). London, UK: Routledge.
doi:10.4324/9780203443408.pt3

Nooteboom, B. (1999): Innovation and inter-firm linkages: New implications for policy. Research Policy, 28, 793-805.
doi:10.1016/S0048-7333(99)00022-0

Nooteboom, B. (2005): Learning and governance in inter-firm relations (Center for Economic Research Discussion Paper No. 2005-38). Tilburg, The Netherlands: Tilburg University.
Retrieved May 15, 2015, from https://pure.uvt.nl/portal/files/773588/38.pdf

OECD (1998): Fostering Entrepreneurship, Paris: OECD.
Last time retrieved June 8, 2016, from:
http://www.oecdilibrary.org/docserver/
download/0498041e.pdf?
expires=1465375685&id=id&accname=oid011481&
checksum=928EDF9734994CB162769CE42C87FA2C

Okamuro, H. (2007): Determinants of successful R&D cooperation in Japanese small businesses: The impact of organizational and contractual characteristics, Research Policy, 36, 1529–1544.
doi: 10.1016/j.respol.2006.12.008

Ostgaard, T. A., Birley, S. (1994): Personal Networks and firm competitive strategy: a strategic or coincidental match?, Journal of Business Venturing, 9, 281-305.
doi:10.1016/0883-9026(94)90009-4

Paier, M. F., Scherngell, T. (2011): Determinants of Collaboration in European R&D Networks: Empirical Evidence from a Discrete Choice Model. Industry and Innovation, 8 (1), 89-104.
doi:10.1080/13662716.2010.528935

Parker, S. C. (2009): The Economics of Entrepreneurship, Cambridge University Press, New York.

Pavitt, K., Patel, P. (1988): Large Firms in the Production of the World's Technology: An Important Case of Non-Globalization, Journal of International Business Studies, 22 (1), 1 – 21.
Stable url: http://www.jstor.org/stable/155237

Penrose, E. G. (1959): The theory of the growth of the firm. New York, NY: Oxford University Press.

Phillips, B. D., Kirchhoff, B. A. (1989): Formation, Growth and Survival, Small Business Economics, 1, 65-74.
doi: 10.1007/BF00389917

Porter, M. (1990): The Competitive Advantage of Nations. Harvard Business Review.

Powell, W. W., Koput, K. W., Smith-Doerr, L. (1996): Interorganizational collaboration and the locus of innovation: Networks of learning in biotechnology. Administrative Science Quarterly, 41, 116-145.
doi:10.2307/2393988

Powell, W. W. (1998): Learning from collaboration: Knowledge and networks in the biotechnology and pharmaceutical industries. California Management Review, 40, 228-240.
doi:10.1002/9780470755679.ch14

Powell, W. W., Grodal, S. (2006): Networks of innovators. In: J. Fagerberg, D. C. Mowery, R. L. Nelson (Eds.), The Oxford handbook of innovation (pp. 56-85). Oxford, UK: Oxford University Press.
doi:10.1093/oxfordhb/9780199286805.003.0003

Pyka, A. (1999): Der kollektive Innovationsprozess, Eine theoretische Analyse informeller Netzwerke und absorptiver Fähigkeiten. Duncker and Humblot, Berlin

Reynolds, P.D. (1997): Who Starts New Firms? – Preliminary Explorations of Firms-In-Gestation, Small Business Economics, 9, 449 – 462.
Stable url: http://www.jstor.org/stable/40228600

Reynolds, P.D., White, S.B. (1997): The Entrepreneurial Process. Economic Growth, Men, Woman, and Minorities, Westport, Conneticut and London, Quorum Books.

Reynolds, P. D. (2000): National Panel Study of U.S. Business Start-ups: Background and Methodology, In: Katz, J. A. (Ed.): Databases for the Study of Entrepreneurship, 153–227, JAI Press, Amsterdam.
Last time retrieved October 21, 2016 from:
http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.199.1529&rep=rep1&type=pdf

Ricardo, D. (1817): On the Principles of Political Economy and Taxation, London: John Murray.

Rogers, E. M., Bhowmik, D. K. (1970): Homophily–heterophily: Relational concepts for communication research. Public Opinion Quarterly, 34, 523-538.
doi:10.1086/267838

Scherer, F.M. (1983): The propensity to patent, International Journal of Industrial Organization, 1 (1), 107 – 128.
doi:10.1016/0167-7187(83)90026-7

Schmoch, U. (1993): Tracing the knowledge transfer from science to technology as reflected in patent indicators. Scientometrics, 26, 193-211.
doi:10.1007/BF02016800

Schumpeter, J. (1912): Theorie der wirtschaftlichen Entwicklung. Eine Untersuchung über Unternehmergewinn, Kapital, Kredit, Zins und den Konjunkturzyklus, Duncker and Humblot, Berlin.

Shane, S. (2000): Prior Knowledge and the Discovery of Entrepreneurial Opportunities, Organization Science, 11, 448-469.
Stable link: http://dx.doi.org/10.1287/orsc.11.4.448.14602

Silverberg, G., Verspagen, B. (1995): An Evolutionary Model of Long Term Cyclical Variations of Catching Up and Falling Behind, Journal of Evolutionary Economics, 5, 209–227.
doi:10.1007/BF01198304

Silverberg, G., Verspagen, B. (1998): Economic Growth as an Evolutionary Process, in: Lesourne, J., Orlean, A. (eds): Advances in Self-Organization and Evolutionary Economics, Economica.

Singh, J. (2005): Collaborative networks as determinants of knowledge diffusion patterns. Management Science, 51, 756-770.
doi:10.1287/mnsc.1040.0349

Smith, A. (1776): The Wealth of Nations, London: Methuen & Co., Ltd.

Solow, R. (1956): A Contribution to the Theory of Economic Growth, Quarterly Journal of Economics, 70, pp 65-94.
doi: 10.2307/1884513

Storey, D.J. (1994): Understanding the Small Business Sector, Thomson Learning.

Stuart, T. E., Hoang, H., Hybels, R. (1999): Inter-organizational endorsements and the performance of entrepreneurial ventures, Administrative Science Quarterly, 44, 315-350.
doi: 10.2307/2666998

Stuart, T. E. (2000): Interorganizational alliances and the performance of firms: A study of growth and innovation rates in a high-technology industry. Strategic Management Journal, 21, 791-811.
doi:10.1002/1097-0266(200008)21:8<791::AID-SMJ121>3.0.CO;2-K

Teece, D.J. (1986): Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy, Research Policy, 15, 285-305.
doi:10.1016/0048-7333(86)90027-2

Ter Wal, A. L. J. (2014): The dynamics of the inventor network in German biotechnology: Geographic proximity versus triadic closure. Journal of Economic Geography, 14, 589-620.
doi:10.1093/jeg/lbs063

Ter Wal, A. L. J., Boschma, R. (2009): Applying social network analysis in economic geography: Framing some key analytical issues. The Annals of Regional Science, 43, 739-756.
doi:10.1007/s00168-008-0258-3

Ter Wal, A. L. J., Boschma, R. (2011): Co-evolution of firms, industries and networks in space. Regional Studies, 45, 919-933.
doi:10.1080/00343400802662658

Thornhill, S. (2006): Knowledge, innovation and firms performance in high- and low-technology regimes, Journal of Business Venturing, 21, 687-703.
doi:10.1016/j.jbusvent.2005.06.001

Tsai, W., Jewell, N. P., Wang, M. (1987): A note on the product-limit estimator under right censoring and left truncation, Biometrica, 74, 4, 883-886.
doi: 10.1093/biomet/74.4.883

Utterback, J. M. (1974): Innovation in Industry and the Diffusion of Technology, Science, 183, 620-626.
doi: 10.1126/science.183.4125.620

Uzzi, B. (1997): Social structure and competition in interfirm networks: The paradox of embeddedness. Administrative Science Quarterly, 42, 35-67.
doi:10.2307/2393808

von Hippel, E. (1987): Cooperation between rivals: informal know-how trading, Research Policy, 16, 291-302.
doi: 10.1007/978-94-009-1075-1_7

von Malmborg, F. (2007): Stimulating learning and innovation in networks for regional sustainable development: the role of local authorities, Journal of Cleaner Production, 15, 1730-1741.
doi:10.1016/j.jclepro.2006.08.014

Wagner, J. (2004): Are Young and Small Firms Hothouses for Nascent Entrepreneurs? Evidence from German Micro Data, ZA Discussion Paper No. 989.
Stable url: http://ssrn.com/abstract=494202

Walker. G.. Kogut. B. Shan. W. (1997): Social Capital. Structural Holes and the Formation of an Industry Network. Organization Science. 8. 109-125.
Stable url: http://www.jstor.org/stable/2635305

Walker, W. E., Harremoes, P., Rotmans, J., Van der Sluijs, J. P., Asselt, M. B. A., Janssen, P., Krayer von Krauss, M. P. (2003): Defining uncertainty: A conceptual basis for uncertainty management in model-based decision support. Integrated Assessment, 4, 5-17.
doi:10.1076/iaij.4.1.5.16466

Walter, S.G., Schmidt, A., Walter, A. (2010): The Patenting Behavior of Academic Founders, Working Paper No. 659399059, Arbeitspapiere des Instituts für Betriebswirtschaftslehre, CAU Kiel.
Last time retrieved June 7, 2016, from:
https://www.econstor.eu/dspace/bitstream/ 10419/37083/4/Patenting-Behavior%20of%20Academic%20Founders.pdf

Wasserman, S., Faust, K. (1994): Social Network Analysis – Methods and Applications, New York, Cambridge University Press.

Williamson, S. (1986): Costly monitoring, financial intermediation and equilibrium credit rationing, Journal of Monetary Economics, 18, 159-179.
doi:10.1016/0304-3932(86)90074-7

Wuyts, S., Colombo, M. G., Dutta, S., Nooteboom, B. (2005): Empirical tests of optimal cognitive distance. Journal of Economic Behavior & Organization, 58, 277-302.
doi:10.1016/j.jebo.2004.03.019

Yang, H., Phelps, C. C., Steensma, K. (2010): Learning from what others have learned from you: The effects of knowledge spillovers on originating firms. Academy of Management Journal, 53, 371-389.
doi:10.5465/AMJ.2010.4938901

Erklärung nach § 4 Abs. 1 PromO

Hiermit erkläre ich,

1. dass mir die geltende Promotionsordnung bekannt ist;
2. dass ich die Dissertation selbst angefertigt, keine Textabschnitte eines Dritten oder eigener Prüfungsarbeiten ohne Kennzeichnung übernommen und alle von mir
3. benutzten Hilfsmittel, persönlichen Mitteilungen und Quellen in meiner Arbeit angegeben habe;
4. dass ich bei der Auswahl und Auswertung des Materials sowie bei der Herstellung des Manuskriptes keine unzulässige Hilfe in Anspruch genommen habe;
5. dass ich nicht die Hilfe eines Promotionsberaters in Anspruch genommen habe und dass Dritte weder unmittelbar noch mittelbar geldwerte Leistungen von mir für Arbeiten erhalten haben, die im Zusammenhang mit dem Inhalt der vorgelegten Dissertation stehen;
6. dass ich die Dissertation noch nicht als Prüfungsarbeit für eine staatliche oder andere wissenschaftliche Prüfung eingereicht habe;
7. dass ich nicht die gleiche, eine in wesentlichen Teilen ähnliche oder eine andere
8. Abhandlung bei einer anderen Hochschule bzw. anderen Fakultät als Dissertation eingereicht habe.

Weimar am 02.11.2016

Tina Wolf

Lebenslauf
Tina Wolf, 27.06.1983

Ausbildung

Bis 06 2002	**Abitur am Hoffmann-von-Fallersleben Gymnasium Weimar (Abschlussnote 2,3)**
10 2002 - 04 2008	**Studium der Volkswirtschaftslehre Schwerpunkt Innovationsökonomik (Abschlussnote 1,9)** Diplomarbeitsthema: Intermediation, Kompatibilität und Reziprozität in regionalen Innovationssystemen (Note 1,3)
05 2008 - heute	**Promotion im Rahmen der DFG RTG 1411 „The Economics of Innovative Change"**

Berufserfahrung

05 2008 - heute	**Wissenschaftliche Mitarbeiterin am Lehrstuhl für Mikroökonomie der Friedrich-Schiller-Universität Jena**
05 2008 – 01 2009	**Thüringer Gründer Studie**
02 2009 – 05 2011	**Begleitende Evaluierung des „Spitzencluster-Wettbewerbs" des BMBF**
06 2011 – 05 2012	Reduktion des Stellenumfangs für die Begleitende Evaluierung des „Spitzencluster-Wettbewerbs" des BMBF im Rahmen der Elternzeit
Seit 06 2012	**Wissenschaftliche und organisatorische Koordination des DFG Graduiertenkollegs „The Economics of Innovative Change"**
Seit 06 2015	**Wissenschaftliche und organisatorische Koordination der Graduate School Human Behavior in Social & Economic Change**

Deutschsprachige Zusammenfassung

Diese Arbeit trägt zu einem besseren Verständnis der Bedeutung von Kooperationen und Wissensaustausch für den Erfolg innovativer Unternehmen bei. Dabei gründet sie im Wesentlichen auf Josef Alois Schumpeters ‚Theorie der wirtschaftlichen Entwicklung' aus dem Jahre 1912. Schumpeter war der erste, der den evolutionären Prozess hinter der Entstehung von Innovationen erkannt und beschrieben hat. Das Bild des Innovators, welches er dabei vor Augen hatte war sicher von Personen wie Gottlieb Daimler oder Werner von Siemens geprägt, die mit Gründung ihres Unternehmens eine Erfindung auf den Markt brachten und damit einen selektiven Wettbewerb anstießen, welcher zur wirtschaftlichen Entwicklung beitrug. Neuere Theorien, wie der ‚resource based view of the firm' (Penrose 1959) oder die ‚knowledge based theory of the firm' (Grant 1996) sehen hingegen einen kollektiven Prozess des Lernens und Umsetzens von neuem Wissen in Innovationen als wesentliche Treiber der wirtschaftlichen Entwicklung (Cantner und Meder 2007, Lundvall 1992, Kogut et al. 1992). Gründe hierfür sind, dass einerseits Innovationsaktivitäten mit einem hohen Unsicherheitsgrad in Bezug auf die Kosten, das Ergebnis und die zeitliche Dimension verbunden sind (Bayona et al. 2001) und andererseits, dass das Wissen der heutigen Zeit eine Komplexität erreicht hat, die es einem einzelnen Akteur nicht mehr erlaubt ohne externe Einflüsse neue Kombinationen des existierenden Wissens zu generieren (Cowan et al. 2006, Haagedorn 2002, Freeman 1991). Somit ist es für Unternehmen, die im innovativen Wettbewerb bestehen wollen von starker Bedeutung bei ihren F&E Anstrengungen zu kooperieren und so externe Ressourcen einzubinden.

Solche Forschungskooperationen sind nicht immer erfolgreich und unterliegen bestimmten Dynamiken. Beide Phänomene (Misserfolg und Dynamiken von Kooperationen) sind bis heute nur unzureichend untersucht worden, nicht zuletzt aufgrund der Komplexität der Fragestellung. Kapitel 2 und 3 der vorliegenden Dissertation widmen sich der Untersuchung bilateraler Forschungsverbindungen im Hinblick auf die Determinanten dieser Phänomene.

Kapitel 2 trägt den Titel ‚*Success and failure of firms' innovation cooperations: the role of intermediaries and reciprocity*'. Dieses Papier wurde zusammen mit Uwe Cantner und Andreas Meder erarbeitet und untersucht anhand von 832

Firmen, inwiefern fehlende Intermediation und Gegenseitigkeit sich auf den Misserfolg von Forschungskooperationen auswirken. Obwohl Kooperationen generell positiv auf die Erfolgsaussichten für F&E-Aktivitäten wirken, stehen der Aufbau und Erhalt ebendieser Beziehungen vor Problemen die sich negativ auf die Generierung neuen Wissens auswirken können. Nehmen wir einmal an, alle existierenden Unternehmen möchten generell ihre F&E-Aktivitäten in Kooperation mit anderen Akteuren durchführen, wir finden aber in der Realität nur ein geringes Maß an F&E-Kooperationen. Ein Grund hierfür kann sein, dass die Unternehmen nicht wissen, wie sie geeignete Partner finden und bewerten sollen. Hier liegt ein so genanntes Intermediationsproblem vor (Cantner und Graf 2003). Dieses Problem ist ähnlich dem Problem der asymmetrischen Information zwischen Kreditgebern und –nehmern auf Finanzmärkten (Williamson 1986). Mit der Suche nach einem geeigneten Kooperationspartner sind hohe Transaktionskosten für die Suche nach potenziellen Partnern und Informationen über deren Wissensbasis und Reputation verbunden. Diese Kosten könnten dazu führen, dass von der Suche nach Partnern Abstand genommen und allein F&E betrieben wird. Intermediäre sind beispielsweise Technologietransferstellen, öffentliche Einrichtung mit der Aufgabe der Kooperationsanbahnung, aber auch Messen, Konferenzen und Mitarbeitermobilität, welche allesamt die Aufgabe haben das Intermediationsproblem zu lösen (Cantner und Graf 2003, Karlsson 1997).

Ein zweiter Grund für die oben angesprochene Zurückhaltung bezüglich kooperativer F&E-Anstrengungen kann das Fehlen von Vertrauen und Gegenseitigkeit in den Kooperationen sein, das so genannte Reziprozitätsproblem (Cantner und Graf 2003). Gouldner (1960), Güth und Yaari (1992) sowie Cialdini und Trost (1998) untersuchten die Prinzipien von Gegenseitigkeit und Fairness ökonomischer Akteure, Phänomene, die auch auf kooperative Erfindungen und Innovationen zutreffen. Kooperationen basieren auf dem urmenschlichen Prinzip der Gegenseitigkeit und können nur funktionieren, wenn beide Partner Wissen austauschen (Fähr und Gächter 2000, Nooteboom 1999). Ist diese Gegenseitigkeit nicht gegeben, so können Kooperationen nicht zustande kommen (ex-ante Reziprozitätsproblem) bzw. werden scheitern (ex-post Reziprozitätsproblem) (Cantner 2000).

Determinanten erfolgreicher Kooperationen wurden in der innovationsökonomischen Literatur bereits breit analysiert (u. a. Katz 1986, Häusler et al. 1994,

Belderbos et al. 2004, Okamuro 2007). Hingegen blieb die Untersuchung von Scheiternsdeterminanten eher unberücksichtigt. Das vorliegende Kapitel widmet sich dieser Forschungslücke und macht einen, wenn auch kleinen, Schritt hin zur empirischen Aufklärung missglückter Kooperationen.
Um die beiden genannten Probleme zu untersuchen, wurden Daten verwendet, die im Rahmen des von der Volkswagen Stiftung finanzierten Projekts ‚Second Order Innovations' erhoben wurden, verwendet. Hierfür wurden 832 Unternehmen aus den regionalen Innovationssystemen Jena, Nordhessen und Sophia Antipolis zu ihren Innovations- und Kooperationsaktivitäten befragt.
Aufgrund der binären oder skalierten Natur der abhängigen Variablen wurden zur Auswertung (geordnete) logistische Regressionen herangezogen.
Die Ergebnisse deuten nicht darauf hin, dass in den untersuchten Regionen ein Intermediationsproblem vorliegt, welches die Kooperationsneigung und den Erfolg mindert. Dennoch konnten die Analysen zeigen, dass innerhalb der Gruppe kooperierender Unternehmen ein positiver Einfluss der empfundenen Bedeutung von Intermediären auf den Kooperationserfolg ausgeht. Dies deutet darauf hin, dass es für Intermediäre wichtig ist von potenziellen Kunden gesehen und für wichtig empfunden zu werden, damit ihre Dienste auch in Anspruch genommen werden.
In Bezug auf das Reziprozitätsproblem zeigt sich, dass fehlendes Vertrauen zum Partner einen wesentlichen Grund für das Scheitern einer Kooperationsbeziehung darstellt.

Kapitel 3 trägt den Titel ‚*The Coevolution of Innovative Ties, Proximity, and Competencies: Toward a Dynamic Approach to Innovation Cooperation*' und wurde zusammen mit Uwe Cantner und Susanne Walter (geb. Hinzmann) erstellt. Anhand von Kooperationsdaten zu deutschen Unternehmen in der Biotechnologiebranche wird die Koevolution von Kooperationsbeziehungen und drei verschiedenen Dimensionen der Nähe zwischen den Partnern dynamisch untersucht. Bei diesen drei Dimensionen der Nähe handelt es sich um kognitive Nähe, soziale Nähe und Ähnlichkeit/Nähe in Bezug auf die Attraktivität des jeweiligen Partners.
Boschma (2005) definiert kognitive Nähe als Unterschied in den Wissensbasen zweier Kooperationspartner. Der Zusammenhang zwischen der Höhe der kognitiven Nähe und der Möglichkeit Wissen auszutauschen nimmt dabei einen

umgekehrt u-förmigen Verlauf an (Nooteboom 1998). Sind die Partner sich in Ihren Wissensbasen zu ähnlich, gibt es vergleichsweise wenig Potenzial zum Wissensaustausch. Sind die Wissensbasen zu weit voneinander entfernt, fehlen absorptive Fähigkeiten um einen Wissensaustausch möglich zu machen. In dem Falle, dass eine Kooperation eingegangen wurde, tauschen die Partner im Zuge ihrer gemeinsamen Forschungsaktivitäten Wissen aus, was ihre kognitive Nähe zueinander erhöht. Das geht so weit bis es keine Potenziale für neue Wissenskombinationen der Partner mehr gibt und aus theoretischer Sicht ein Abbruch der Kooperation sinnvoll erscheint.

Soziale Nähe geht mit Vertrauen, sozialen Normen und Kontrolle über unerwünschtes Verhalten einher (Boschma 2005, Granovetter 2005, Walker et al. 2003) und beeinflusst ebenso den Fortgang einer Kooperationsbeziehung, aber eher umgekehrt (Dahlander und McFahrland 2013, Gulati 1995). Je höher die soziale Nähe zwischen zwei Kooperationspartnern, desto eher wird ihre Kooperationsbeziehung fortbestehen.

Frühere Studien haben gezeigt, dass die Attraktivität als Kooperationspartner durch Erfahrung mit Innovationen und Kooperationen erhöht wird (Ahuja 2000, Gulati 1999, Stuart 2000). Dies hängt auch damit zusammen, dass Kooperationen und der Umgang mit den Rechten am entstandenen Wissen nicht trivial sind und sich gemachte Erfahrungen positiv auf den Erfolg zukünftiger Kooperationen auswirken. Kooperationen von Partnern mit Vorerfahrungen haben daher, im Vergleich zu Kooperationen unerfahrener Partner, eine erhöhte Wahrscheinlichkeit erfolgreich zu sein und fortzubestehen.

Im zeitlichen Verlauf einer Kooperationsbeziehung entwickeln sich die kognitive und die soziale Nähe der Partner aufeinander zu bzw. werden größer (Broekel 2015, Balland et al. 2015, ter Wal 2014). Auch die Erfahrung der Partner verändert sich im Zeitverlauf. Bisherige Untersuchungen haben diese Dimensionen anhand eines statischen Ansatzes aufgearbeitet. Kapitel 3 dieser Arbeit löst sich davon und untersucht den Zusammenhang zwischen den genannten Dimensionen der Nähe und der Entwicklung der Kooperation unter Zuhilfenahme eines dynamischen Ansatzes. 321,683 potenzielle Kooperationspaare werden über einen Zeitraum von 32 Jahren beobachtet und dabei die Auswirkung der Veränderung der drei Nähedimensionen auf die Kooperationsentstehung, -fortführung und -beendigung analysiert. Die Daten hierfür stammen von der OECD REGPAT Database (Januar 2012).

Da es sich bei der Entscheidung zu einem bestimmten Zeitpunkt mit einem bestimmten Akteur zu kooperieren um eine binäre Entscheidung handelt, wird ein logistisches random-effects panel model angewendet, welches 1,000-fach repetiert wurde.

Die deskriptive Analyse zeigt, dass das Wiederholen von Kooperationen nicht zum ‚normalen' Verhalten der Unternehmen in der Stichprobe gehört. Vielmehr werden die Partner häufig gewechselt, eine Beobachtung welche auch Cantner und Graf (2006) machen. Auf Ebene der kognitiven Nähe wurden die drei Dimensionen overlap, reciprocal potential und knowledge transfer untersucht. Es zeigt sich, dass ein großer overlap der Wissensbasen in Verbindung mit einem geringeren reciprocal potential die Wahrscheinlichkeit erhöht, dass ein potenzielles Kooperationspaar tatsächlich eine Kooperationsbeziehung eingeht. Soziale Nähe hingegen scheint in der vorliegenden Datenbasis keine Rolle für dynamische Entwicklungen in den Kooperationsbeziehungen zu spielen. Vorerfahrungen mit Kooperationen hingegen haben dann einen positiven Einfluss auf die Kooperationswahrscheinlichkeit, wenn beide Partner ein hohes Maß davon mitbringen.

Verlässt man die Ebene bilateraler Kooperationsbeziehungen und betrachtet die Gesamtheit der vorliegenden Kooperationen (ob in einer Branche, einer Technologie oder einer Region), so stößt man auf die Ebene der Innovationsnetzwerke. Kapitel 4 und 5 der vorliegenden Dissertation bewegen sich auf diesem Terrain und analysieren die Rolle von Innovationsnetzwerken für den Erfolg und das Überleben junger Unternehmen.

Ein wichtiger Motor für die wirtschaftliche Entwicklung sind Innovationen (Pyka 1999). Innovationen sind allerdings in der Regel das Ergebnis eines komplexen Prozesses und der Rekombination von neuem und altem Wissen, welcher ohne kollektive, soziale Prozesse kaum mehr möglich ist (Lundvall 1992, Doloreux und Parto 2005, Jaffe 1986, Bagchi-Sen 2002). Diese interaktiven Kontakte zwischen Angestellten von Unternehmen, Forschungsinstituten oder Universitäten bilden ein komplexes Netzwerk von Akteuren, die Innovationen generieren und diese entweder mit einem existierenden Unternehmen oder durch die Gründung eines neuen Unternehmens auf den Markt bringen. Dieses soziale Netzwerk ist das so definierte Innovatorennetzwerk nach Cantner und Graf (2007).

Das gemeinsam mit Uwe Cantner verfasste Kapitel 4 trägt den Titel ‚*On regional innovator networks as hubs for innovative ventures*' und untersucht, inwiefern sich die Verbindung zu einem solchen Innovatorennetzwerk auf die Überlebenschancen junger Unternehmen auswirkt. Hierfür werden Handelsregisterdaten und Patentdaten für 2,199 Thüringer Unternehmen, die in den Jahren 1993-2004 gegründet wurden, analysiert. Da es sich bei der gemessenen Erfolgsvariable um eine Überlebenswahrscheinlichkeit (hazard rate) handelt, wird Cox's proportional hazards model (1972) angewendet, ein Modell welches speziell für die Untersuchung von Überlebensdaten entwickelt wurde.
Der erste Teil der Analyse zeigt, dass sich der verwendete Datensatz verhält wie die von anderen Forschern verwendeten Datensätze auch. Innovationen erweisen sich generell als Erfolgsgarant für Unternehmen. In einem zweiten Schritt wurde für 442 innovative Unternehmen untersucht, inwiefern sich deren Erfolg unterscheidet, wenn sie isoliert oder verbunden mit dem Netzwerk innovieren. Die Analysen zeigen, dass innovative, mit dem Innovatorennetzwerk verbundene Unternehmen vergleichsweise höhere Überlebenschancen aufweisen.

Kapitel 5 mit dem Titel ‚ *The selective nature of innovator networks: from the nascent to the early growth phase of the organizational life cycle*' wurde ebenfalls mit Uwe Cantner gemeinsam erarbeitet und untersucht anschließend an die Erkenntnisse aus Kapitel 4, welche Netzwerkstruktur und Positionen im Netzwerk vorteilhaft für die Überlebenschancen der Unternehmen sind. Diese Zusammenhänge können allerdings nicht unabhängig vom Lebenszyklus des Unternehmens betrachtet werden (Hite und Hesterly 2001). In den ersten drei Phasen des Lebenszyclus, namentlich der Nascent-Pase, der Emergence-Phase und der Early-Growth-Phase wirken Netzwerkstruktur und Position im Netzwerk unterschiedlich auf die Überlebenschancen des Unternehmens. Wissenspillover sind ein wesentlicher Aspekt bei der Generierung von Innovationen und der Realisierung technologischer Potentiale (Meagher und Rogers 2004, Feldman und Audretsch 1999, Griliches 1992). Diese Wirkung basiert auf Wissensspillovers aus dem Netzwerk. Für die Innovationsleistung von Unternehmen die mit einem Innovatorennetzwerk verbunden sind, spielt die Struktur jenes Netzwerkes eine entscheidende Rolle. In Abhängigkeit der Netzwerkstruktur können Wissenspillover vereinfacht oder behindert werden. In

Netzwerken mit einem hohen Fragmentierungsgrad können Wissenspillover nur vergleichsweise schlecht zwischen den einzelnen Netzwerkakteuren fließen, wohingegen in eng verstrickten Netzwerken viele Wissensflüsse möglich sind (Gilsing et al. 2008, Fershtman und Gandal 2011, Meagher und Rogers 2004). Allerdings sind sehr dichte Netzwerke mit hohen Kosten für die Kontaktpflege, einer hohen Gefahr von unerwünschtem Wissensabfluss und wenigen Möglichkeiten für neue Wissenszuflüsse verbunden (Gilsing und Nooteboom 2005, Burt 1992, Gilsing et al. 2008). In den verschiedenen Phasen des Unternehmenslebenszyklus wirken sich diese Prozesse unterschiedlich aus. Während der Nascent-Phase spielen für das Überleben andere Faktoren, wie die Aufbringung von ausreichend Startkapital, Erfahrung in dem Sektor und Gründungserfahrung eine übergeordnete Rolle (Cantner und Stuetzer 2013). Hingegen wird es nach der formalen Gründung des Unternehmens, also in der Emergent-Phase, umso wichtiger zu einem engen Innovatorennetzwerk verbunden zu sein und dort enge Kontakte zu pflegen. So kann das neue Unternehmen möglichst viele Informationen aus dem Netzwerk akquirieren und absorbieren. Enge Netzwerke gehen allerdings mit einem hohen Risiko für Redundanzen und unerwünschte Wissensabflüsse einher. Das ist anfangs noch gut, denn so kann das neue Unternehmen möglichst viele Informationen, auch von Konkurrenten erhalten. Im Laufe der Entwicklung, wenn sich das Unternehmen am Markt etabliert hat, ist es dann vorteilhaft Redundanzen zu reduzieren und den eigenen Wissensabfluss zu minimieren. Somit wandelt sich der Bedarf des Unternehmens nach einem engen Netzwerk im Laufe der ersten beiden Phasen des Lebenszyklus hin zu einem möglichst fragmentierten Netzwerk, welches viele Möglichkeiten zur Kontrolle der Wissensflüsse bietet (Hite und Hesterly 2001, Burt 1992).

Doch nicht nur die Struktur des Netzwerkes zu dem ein Unternehmen verbunden ist, sondern auch die Position im Netzwerk spielt eine entscheidende Rolle. Ist ein Akteur sehr zentral im Netzwerk, so besitzt er viele Kontakte, ist quasi prominent (Wasserman und Faust 2009). In einer solchen Position kann der Akteur von zahlreichen Wissenszuflüssen profitieren und im besten Fall sogar noch steuern, welches Wissen im Netzwerk welche Wege nimmt (Gilsing et al. 2008). Sehr oft besteht ein Netzwerk aus mehreren kleineren Unternetzen, die nicht notwendigerweise miteinander verbunden sind (Wasserman und Faust 2009). Innerhalb jedes dieser Netzwerke gibt es Wissensflüsse, wobei davon ausgegangen werden kann dass die meisten davon in der Hauptkomponente (der größten miteinander verbundenen Gruppe im Netzwerk) zu finden sind (Powell et al. 1996). Burt (1992) spricht von einer möglichen Brückenfunktion von Akteuren im Netzwerk. Sind zwei Komponenten nur über einen einzelnen Akteur miteinander verbunden, so besitzt dieser quasi die Macht über das zwischen den beiden Komponenten ausgetauschte Wissen. Auch für die Rolle des Ego-Netzwerks für das Überleben eines jungen Unternehmens sind Veränderungen im Laufe des Unternehmenslebenszyklus zu erwarten. Während ein dichtes Ego-Netzwerk in der Emergent-Phase von Vorteil ist, genießen in der Early-Growth-Phase Unternehmen mit einem auf sie selbst zentralisierten Netzwerk Vorteile bezüglich Ihrer Überlebenschancen.

Ebenso, wie im Kapitel 4 werden Daten aus dem Thüringer Handelsregister und vom Deutschen Patent- und Markenamt für die Analyse verwendet. Auch in Kapitel 5 wir als Erfolgsvariable die Überlebenswahrscheinlichkeit (hazard rate) für die Unternehmen gemessen und Cox's proportional hazards model (1972) geschätzt.

Die Ergebnisse weisen auf einen umgekehrt u-förmigen Zusammenhang zwischen der Dichte des jeweiligen Netzwerks und der Sterbewahrscheinlichkeit der Unternehmen hin. Somit sind sowohl dichte, als auch fragmentierte Netzwerke von Vorteil, nicht aber eine Kombination der beiden. Burt (1992) und Coleman (1988) hatten somit womöglich beide Recht. In Bezug auf die Netzwerkposition erweist sich die Mitgliedschaft in der Hauptkomponente als negativer Einflussfaktor für das Überleben von Unternehmen.

In den Kapiteln 4 und 5 gelingt es erstmals das Innovatorennetzwerk als internes Charakteristikum des Unternehmens zu betrachten und zu analysieren, eine Forschungslücke deren Schließung mit den beiden vorliegenden Kapiteln ein Stück näher gekommen wird. Mit Hilfe der Namen der Unternehmensgründer und der Patentanmelder werden die Patente des Unternehmens identifiziert, ein Ansatz, der insbesondere bei kleinen, jungen Unternehmen sinnvoll ist. Unternehmensgründer melden häufig Patente für das Unternehmen auf den eigenen Namen an, damit diese im Falle eines Scheiterns nicht in die Insolvenzmasse fließen (siehe auch Kapitel 6 dieser Dissertation). Mit Hilfe der Patentdaten wurden dann Innovatorennetzwerke für die von Granato und Farhauer (2008) identifizierten Arbeitsmarktregionen in Thüringen erstellt. In Anlehnung an die

Untersuchungen von Murray (2004) wurde dann davon ausgegangen, dass der Unternehmensgründer sein soziales wissenschaftliches Netzwerk in das wissenschaftliche Netzwerk des Unternehmens überträgt und damit das Unternehmen über den Gründer mit dem Innovatorennetzwerk verbunden ist.

Das abschließende Kapitel der Dissertation trägt den Titel ‚*Innovative start-up patenting: a new approach towards identification and determinants*' und wurde in Alleinautorenschaft verfasst. In den Kapiteln 4 und 5 wurde anhand von Patentdaten bereits der Einfluss des Innovatorennetzwerks auf innovative Unternehmensgründungen untersucht. Eine deskriptive Analyse der Befragungsdaten aus der Thüringer Gründer Studie zeigt jedoch, dass die Anmeldung von Patenten für junge, kleine Unternehmen ein sehr seltenes Ereignis ist. Von 534 Unternehmen, die in innovativen Branchen tätig sind (Grupp et al. 2000) meldeten nur etwa 64 (12%) Patente an. Zwar gibt es einige Forschungspapiere, die sich mit der Patentierungsneigung von Unternehmen beschäftigen (z.B. Scherer 1983, Bound et al. 1984, Brouwer und Kleinknecht 1999, Blind et al. 2006, Hall et al. 2012), sie tun dies allerdings vorwiegend anhand von Daten etablierter, größerer Unternehmen. Eine detaillierte Analyse der Patentierungsneigung für kleine, junge Unternehmen, die in der Regel weniger als 10 Mitarbeiter haben wurde bis heute noch nicht veröffentlicht. Das vorliegende Kapitel 6 schließt ebendiese Forschungslücke und untersucht die Determinanten der Patentierungsneigung junger und innovativer Unternehmen in Thüringen. Darüber hinaus wendet die Analyse auch eine bisher nicht beachtete Identifizierungsstrategie für die Patente junger Unternehmen an. Von den 64 Unternehmen im Datensatz, die Patente angemeldet haben, haben gerade einmal 5,5% das Patent auf den Namen des Unternehmens angemeldet. Alle weiteren Patente liefen auf die Namen der Unternehmensgründer. Deshalb wurden -unter der Annahme dass die Gründer ihre Patente im Rahmen ihres Unternehmens Kommerzialisieren wollen- für die Analyse auch Patente der Gründer in Betracht gezogen.

Die Ergebnisse zeigen, dass Vorerfahrungen in der Patentierung, Kooperationen, F&E-Förderung und Wissenschaftsorientierung positive Determinanten der Patentierungsneigung junger Unternehmen sind.